SAFETY ASSESSMENT OF FREEWAY MERGING AND DIVERGING INFLUENCE AREAS BASED ON CONFLICT ANALYSIS OF SIMULATED TRAFFIC

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Thesis directed by Professor Bruce N. Janson.

ABSTRACT

The safety of merging and diverging influence areas, intersections, interchanges, and other traffic facilities is assessed by tracking and analyzing police-reported motor vehicle crash records. Since the nature of road crashes is random and infrequent, this process is slow to reveal the need for remediation of the roadway design and traffic control strategy. Moreover, this process is not applicable to assess new designs that have not yet been built, or deployed in the real world.

This study summarizes a technique combining micro-simulation and automated conflict analysis to assess the safety of traffic facilities without waiting for a statistically above-normal number of crashes to occur. The technique is also valuable in assessing the relative performance of one design versus another. Traffic Conflict Technique (TCT) is among the most common surrogate measures to study the safety of roadway facilities. The software referred to as Surrogate Safety Assessment Model (SSAM) was developed by FHWA and was used in this study. The SSAM software

application was designed to perform statistical analysis of vehicle trajectory data. Trajectory data is the output from microscopic traffic simulation models. Among the various traffic simulation modeling tools, VISSIM was chosen because of its compatibility with SSAM, its versatility for analyzing networks of big sizes and its ability to provide users with the capability to model any type of geometric configurations.

Forty-two merging and forty-two diverging influence areas in Colorado, USA, were modeled in VISSM and conflict analysis was performed using SSAM under AM-peak traffic conditions. Five field validation tests were conducted. Conflicts predicted by SSAM approach were compared with actual crash records at merging and diverging influence areas in all statistical validation tests. The results of the validation effort of safety assessment based on conflict analysis of simulated traffic suggested that this technique is recommended for safety assessment at merging and diverging locations.

This abstract accurately represents the content of the candidate's dissertation. I recommend its publication.

Signed ______________________

Bruce N. Janson

DEDICATION

I dedicate this thesis to my loving and devoted wife, Azeb, for her unfaltering support and understanding while I was completing it. I also dedicate this to my daughters Yohana, Heldana, and Yosabet and to my parents who gave me an appreciation of learning and taught me the value of perseverance and resolve.

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My thanks to each of the members of my doctoral committee for their support during the completion of this thesis.

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1. Introduction

1.1 Background

According to the National Highway Traffic Safety Administration (NHTSA 2006) report, motor vehicle travel is the primary means of transportation in the United States, providing an unprecedented degree of mobility. Despite all its advantages, deaths and injuries resulting from motor vehicle crashes are the leading cause of death for people of every age from 2 through 34. Traffic fatalities accounted for more than 90 percent of transportation-related fatalities.

National Highway Traffic Safety Administration (NHTSA 2009) stated that in the United States more than 5.5million police-reported motor vehicle crashes occurred. Of these 1.5million (28%) crashes resulted in an injury, 30,797 (fewer than 1%) resulted in a death and 3.4million (73%) involved in property damage only. The fatality rate per 100 million VMT was 1.03.

There were 8.6million vehicles involved in single and two-vehicle crashes. The number of vehicles involved in a merging/lane changing maneuver were 312,000 (3.6%). Resulting from these maneuvers were 769 fatalities, 48,000 injury, and 263,000 property damage only crashes. Similarly, the number of vehicles involved in a going straight maneuver was 4.3million (50.4%). Resulting from these were 27, 124 fatalities 1.25million injury, and 3.0million property damage only.

The World Health Organization (2004) projected that between 2004 and 2030 global deaths increase by 28% which is predominantly due to the increasing number of road traffic accident deaths. Road traffic accident deaths are projected to increase from 1.3 million in 2004 to 2.4 million in 2030, primarily due to the increased motor vehicle ownership and use associated with economic growth in low- and middle-income countries. Road traffic accidents are projected to rise from the ninth leading cause of death globally in 2004 to the fifth in 2030. According to the United Nations General Assembly (2008), by 2020 road traffic deaths and injuries will exceed HIV/AIDS as a burden of death and disability.

1.2 Traffic Safety Overview

A traffic accident occurs when a road vehicle collides with any physical object and results in injury, property damage, and death. Factors contribute to the risk of collision include; vehicle design, speed of operation, road design, and driver impairment. Worldwide motor vehicle collisions lead to significant death and disability as well as significant financial costs to both society and the individual.

For the last two decades, several legislations have been making safety a central, explicit, comprehensive, and integrated part of transportation planning. As a result of this, safety management systems have advanced to a great extent. Traffic safety data and analytical tools have been improved and refined, and the effects of countermeasures have become better understood.

Since 1991 there have been three major Acts announced in the Unites States of America: (1) the 1991 Intermodal Surface Transportation Efficiency Act (ISTEA); (2) the 1998 Transportation Equity Act for the 21st Century (TEA-21), and (3) the 2005 Safe, Accountable, Flexible, Efficient Transportation Equity Act (SAFETEA-LU.)

The Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 moved the historical focus of highway and transit programs away from construction, capacity, and congestion. The Act changed the emphasis towards mobility and access, system performance, and consideration for the environment and quality of life.

The Act did not specifically mention safety as part of the planning process but mandated six comprehensive management systems including a Safety Management System (SMS) as a prerequisite for funding. The SMS was part of the strategy to improve the management, operations, and safety of the highway system through improved data analysis and collection, through improved coordination, cooperation, and communication among agencies, and through the development of collaborative strategic plans (Depue 2003).

In 1998, the Transportation Equity Act for the 21st Century (TEA-21) called for comprehensive safety consciousness. The Act required state DOTs (and MPOs) to increase the safety and security of the transportation system for motorized and non-motorized users. This was the first time that safety became an explicit part of transportation plans. Prior to TEA-21, safety was sometimes a prominent factor in project development and design, but this legislation calls for safety consciousness in a more comprehensive, system-wide, multimodal context, (FHWA 2001a).

The Safe, Accountable, Flexible, Efficient Transportation Equity Act (SAFETEA-LU) became law in 2005. SAFETEA-LU has a strong focus on integrated and comprehensive safety planning. It was built on previous legislation in giving specific and increasing recognition to safety issues.

The Act establishes the Highway Safety Improvement Program (HSIP) as a core program and nearly doubles the funds available for infrastructure safety and comprehensive strategic highway safety planning. The purpose of the HSIP is to reduce fatal and serious/life changing crashes. The program includes planning, implementation, and evaluation of safety programs and projects. (Bahar, G., and Morris, N. (2007)).

Generally, these legislations have encouraged or insisted on giving safety priority through better data, better analysis, better reporting systems, and the adoption of a structured comprehensive approach. A detailed study of the safety of highways would help to understand safety and help to make safety legislation a success.

1.3 Statement of the Problem

Until recently the safety of merging and diverging influence areas, intersections, interchanges, and other traffic facilities is most often assessed by tracking and analyzing police-reported motor vehicle crashes over time. Since the nature of crashes is random and infrequent, the process of analysis of safety based on the police report is slow to reveal the need for remediation of either the roadway design or the flow-control strategy. This process is also not applicable to assess new designs that

have yet to be built, or to assess new flow control strategies before they are employed on-site.

This study summarizes a technique combining micro-simulation and automated conflict analysis to assess the safety of traffic facilities without waiting for a statistically above-normal number of crashes to occur. The technique is also valuable in assessing the relative performance of one design versus another in comparing alternative designs.

1.4 Research Objectives and Contributions to the Transportation Industry

The objective of this research was to assess the safety of freeway merging and diverging influence areas using conflict analysis technique and compare the results with the actual crash experience. SSAM conflict analysis software was used for predicting safety performances at the predefined locations. The Surrogate Safety Assessment Model (SSAM) is a software application designed to perform statistical analysis of vehicle trajectory data output from microscopic traffic simulation model, in this study VISSIM.

VISSIM is a traffic simulation modeling tool which was chosen because of its compatibility with SSAM, its versatility for analyzing networks of big sizes and its ability to provide users with the capability to model any type of geometric configurations or unique operation/driver behavior encountered within the transportation system. It is a time-based microscopic simulation tool that uses various driver behavior and vehicle performance models to accurately

represent urban traffic and public transport operations. This study identified areas in need of further research.

The study will make the following contributions to the industry:

- Helps in assessing the relative safety performance of one design versus another.
- Provide transportation agencies, planners, engineers, researchers with information about the type, frequency and relative location of conflicts.
- Provide solution that improves safety, access, and mobility of the merge/diverge influence area.
- Provide the safety analyst with a fast report to reveal the need for remediation of the roadway design.

1.5 Glossary of Terms – Quick Reference Guide

Accident (traffic): Event between road-users that results in injury, fatality or property damage.

Accident causation: Underlying reasons that pre-empt a traffic accident, most usually involving an unforeseen chain-of-events. Accident causation is often attributed to one of the three main components of the traffic system: road-user, vehicle or roadway, or a combination of thereof.

Accident outcome: Result of an accident in terms of injury severity, fatality and in some cases also property damage.

Accident rate: Number of accidents in accordance with a measure of exposure.

Accident severity: Level of injury sustained in a traffic accident: usually categorized as minor, serious or fatal.

Calibration: Process used in Traffic Simulation to (statistically) ensure that the functioning and behavior of a particular model and/or sub-model corresponds with observed empirical measurements or predetermined values.

Car-following: Term used to describe the status of a vehicle that has a time/distance gap or headway less than a predetermined maximum value.

Collision: Impact event between two or more road-users/vehicles, or a road-user (vehicle) and stationary object.

Collision course: Existence of a common projected conflict point in time and space for two (or more) road-users/vehicles, usually based on momentary measures of trajectory, speed and distance.

Conflict: An observable situation in which two or more road users approach each other in time and space to such an extent that there is risk of collision if their movements remain unchanged.

Conflict distance: A momentary measurement of (spatial) distance to a common conflict point for a road-user/vehicle in a conflict situation.

Conflict point: Common spatial location of projected trajectories given momentary measures of speed and distance for two or more road-users/vehicles.

Conflict severity: Seriousness of a potential collision or near-accident measured by temporal or spatial proximity.

Conflict speed: Momentary measurement of velocity for a road-user (vehicle) in a conflict situation.

Conflict zone: Common area used by road-users/vehicles approaching from different trajectories.

Crash: Term that is sometimes preferred to (traffic) accident due to the fact that it implies an element of causality rather than an unforeseen random occurrence.

Driver behavior: Largely misused and over-simplified term used in traffic engineering that is used to describe the actions and/or variability of drivers in different driving situations. It should relate to the study of individual behavioral processes that underlie driver actions (performance).

Exposure: Measure of spatial or temporal duration in the traffic system in relation to the number of dynamic system objects road-users, vehicles (axles), etc.

Fatality: Death resulting from a traffic accident (usually within a 30 day period after the accident occurrence).

Gap-acceptance: Process that describes and measures interaction between prioritized and non-prioritized road-users. Generally involves spatial or temporal measurement of gaps or lags in prioritized streams that are accepted or rejected in relation to a particular yielding maneuver.

Incident: the term used in a more abstract sense to refer to either crashes or conflicts.

Injury accidents: Traffic accidents that result in minor or serious injury to one or more parties.

Macroscopic (macro-) simulation: Simulation at a less detailed (aggregated, macroscopic) level.

Microscopic (micro-) simulation: Simulation at a very detailed (microscopic) level.

PET: It is the minimum post-encroachment time observed during the conflict. Post encroachment time is the time between when the first vehicle last occupied a position and the time when the second vehicle subsequently arrived to the same position. A value of zero indicates a collision. A post-encroachment time is associated with each time step during a conflict. A conflict event is concluded when the final PET value is recorded at the last location where a time-to-collision value was still below the critical threshold value. This value is recorded in seconds.

Police reported accidents: Accidents that are reported by the police and are recorded in the accident database of accident.

Safety: Freedom from accident or loss.

Simulation (traffic): Abstract imitation of the operation of a real-world process or system over time and event occurrence. Traffic simulation is concerned with the modeling of processes in the traffic system and can be conducted at different levels of abstraction depending on the purpose of the study.

TTC: It is the minimum time-to-collision value observed during the conflict. This estimate is based on the current location, speed, and future trajectory of two vehicles at a given instant. A TTC value is defined for each time step during the conflict event. A conflict event is concluded after the TTC value rises back above the critical threshold value. This value is recorded in seconds.

1.6 Study Workflow Structure

Figure 1.1 illustrates Study Workflow Structure. Accordingly, this research is divided into three Parts. Part 1 included introduction, information and data search. It consists of Chapter 1 and Chapter 2. Chapter 1: Introduction, it provided an introduction to the study by presenting the background information, traffic safety overview, statement of the problem, study objectives and contributions to the transportation industry; and glossary of terms. Chapter 2: Literature Review: a comprehensive literature review on the safety performance of merging and diverging influence areas from published information was provided. It presented the overview of the merging and diverging movements on freeways, the survey and collection of available modeling data, background of safety on freeway speed change locations, regression models, Bayesian accident-prone locations, and simulation and conflict analysis tools. Also preliminary qualitative analysis of the data was carried out to identify the general validity of the selected variables. Part 2 included data analysis. It consists of Chapter 3: Research approach and methodology, this section described the study methodology used in the field validation test and the steps taken to complete the study. Part 3 consists of Chapter 4 and Chapter 5. Chapter 4: Test results and discussion, this section validated the actual crash data and discussed the results of the analysis. Chapter 5: Presented the summary, conclusions and recommendations drawn from the results of the study.

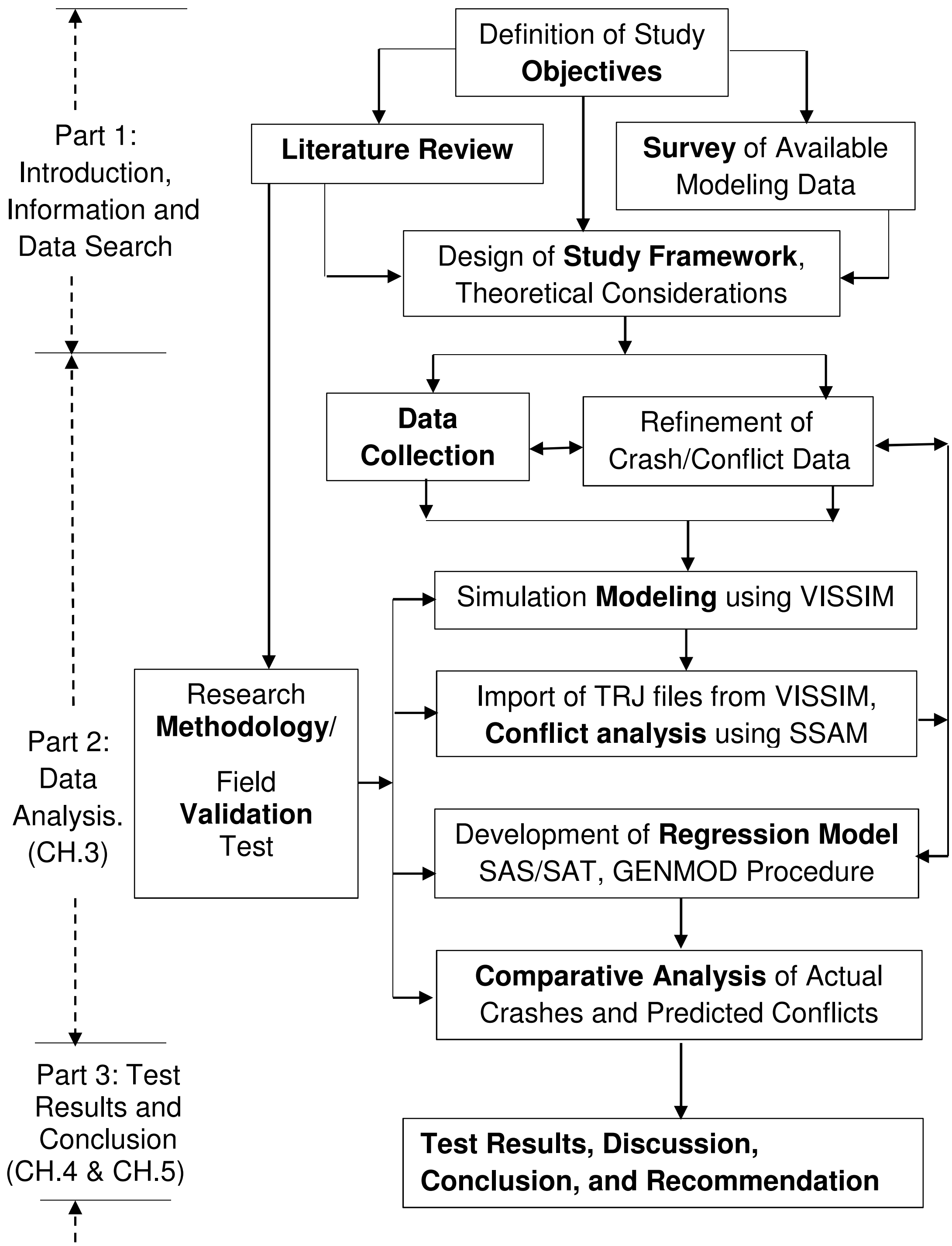

FIGURE 1.1 STUDY WORKFLOW STRUCTURE

2. Review of the Literature

2.1 Traffic Conflict Technique

According to Amundsen and Hyden (1977), a conflict is defined as an observable situation in which two or more road users approach each other in time and space to such an extent that there is risk of collision if their movements remain unchanged.

The traffic conflict technique method initially developed at the Detroit General Motors laboratory in the late 1960's for identifying safety problems (Perkins and Harris, 1968). It was based on observer judgments using time-lapse filming, and proves a costly and time consuming technique. They correlated conflict patterns to accident types. Spicer (1973) studied about the safety of six intersections and concluded that there was good correlation between serious conflicts and reported injury accidents. Sayed (1997) conducted a study to estimate the safety of un- signalized intersections using traffic safety technique. A computer simulation model was used to study traffic conflicts with time-to-collision as the critical traffic event in simulating driver behavior. Using the data collected from 30 conflict surveys, he established traffic conflict frequency and severity standards for un-signalized intersections. These standards allow the relative comparison of the conflict risk at various intersections. Miglez et al. (1985) developed a methodology to predict traffic accidents from observed conflicts. Also, statistical procedures were developed to determine conflict rate values that could be considered "abnormally" high. The study concluded that traffic conflicts are good

surrogates of accidents in that they produce estimates of average accident rates nearly as accurate as those produced from historical accident data.

Gettman, Pu, Sayed, and Shelby (2008), studied a method of safety assessment utilizing a traffic conflicts analysis technique applied to simulation models of intersections, interchanges, and roundabouts. They developed a software application to automate the task of traffic conflicts analysis and conducted validation testing to gauge the efficacy of the assessment method.

Several surrogate traffic conflict measures have been developed to assess the safety of highway facility. The common surrogate conflict measures are gap time, encroachment time, deceleration rate, proportion of stopping distance, post-encroachment time, initially attempted post-encroachment time, and time-to-collision.

There is general consensus that higher rates of traffic conflicts can indicate lower levels of safety for a particular facility, given the fact that conflicts generally result from a lack or misunderstanding of communication between the different road users (Risser 1985 and Archer 2000)

In this study, traffic conflicts occur with adequate frequency to overcome the statistical challenges posed by infrequent crashes. Also, since adequate conflict data can be collected in a relatively short time, conflict analysis is not subject to the problem of changing of the underlying conditions (e.g., traffic volumes, geometry) that affect long-term crash records.

2.2 Merging and Diverging Movements on Freeways

According to Roess, R., Prassas, E., and McShane W. (2004), merging occurs when two separate traffic streams join to form a single stream. Merging can occur at on-ramps to freeways or multi-lane highways, or when two significant facilities join to form a single traffic stream. Merging vehicles often make lane changes to align themselves in lanes appropriate to their desired movement. Diverging occurs when one traffic stream separates to form two separate traffic streams. This occurs at off-ramps from freeways and multilane highways, but can also occur when a major facility splits to form two separate facilities. Again, diverging vehicles must properly align themselves in appropriate lanes, thus indicating lane-changing; non-diverging vehicles also make lane changes to avoid the turbulence created by diverge maneuvers.

Therefore, a merge area would always follow an on-ramp whereas a diverge area would always precede an off-ramp. Road users in such areas are required to select and adjust speeds without causing undue hazards to themselves or to other road users. Such hazards would normally increase in terms of frequency and intensity with increasing volumes of vehicles entering and exiting a specific segment on the freeway. This increase may result from the combination of increasing number of required lane changes and decreasing probability of a suitable gap between moving vehicles to perform a merge or diverge operation (Sarhan, M.; Hassan, Y.; and Abd El Halim, A.O. 2008).

2.3 Survey of Modeling Data

Since the nature of road crashes is random, the choice of the analysis period has a significant impact on the accuracy and reliability of the safety assessment. Accident counts that are recorded for overly extended time period may introduce biases in the analysis when current traffic and geometric conditions differ from those prevailing when the crashes occurred. Similarly, an overly short period reduces the number of crashes considered and hence the statistical accuracy of the model would be affected. According to the Permanent International Association of Road Congresses PIARC (2003) Road Safety Manual, the minimum accepted analysis period is 3 years. For this study, a three year data from year 2008 through 2010 was used which was obtained from the Colorado Department of Transportation (CDOT) accident database.

The greatest statistical challenge of the safety assessment of a facility in accurately pinpointing an underlying crash rate is the nature of motor vehicle crashes. Crashes are so infrequent and exhibiting variable hourly and yearly crash counts. The problem is increasingly difficult for areas with lower (more infrequent) crash rates. There is possible bias in comparing peak-hour conflicts to annual crashes. The statistical models that correlate the peak-hour crash with the peak hour conflict on the merging and diverging locations may not converge as there are too few peak-hour crashes (which are less than 25% of the total crashes). Field validation through estimation with a larger data set would result in a more significant parameters estimates and more accurate crash prediction.

Twenty-one interchanges, forty-two merging and forty-two diverging influence areas were selected. A preliminary assessment was made of the types of interchange elements that were in sufficient numbers and had sufficient data available for statistical modeling of accidents to be conducted. Accordingly diamond interchange configurations were selected.

Using each interchange's milepost as a common identifier, modeling data was collected for each interchange taking the following into consideration:

1. Interchange layout: number of lanes on mainline and ramps, ramp length, and ramp configuration.
2. Traffic volumes: average daily traffic (ADT), design hourly volume (DHV), percent trucks, and on-ramp hourly traffic volume recorded by ramp meters.
3. Data on crash frequency on mainline and ramps.
4. Location of crash occurred on the highway. Only crashes at the merge and diverge influence areas of the interchange were considered.
5. Accident Type: accidents were regrouped into three: rear-end, crossing and lane-changing. Only vehicle-to-vehicle accidents were considered.
6. Direction: the direction of traffic flow at the time of crash: North, Northeast, Northwest, East, West, South, Southeast, Southwest.

2.4 Interchanges and Ramps

Grade separation of intersecting roadways reduces crashes caused by crossing and turning movements. An interchange is a system of interconnecting roadways in conjunction with one or more grade separations that provides for the movement of traffic between two or more roadways or highways on different levels. Access control is a highly desirable feature

along the crossroad at an interchange to provide efficient traffic operations and safety. The most common roadways connections at an interchange consist of freeway-to-freeway (access-controlled freeways), freeway-to-arterial and arterial-to-arterial. Freeway-to-arterial and arterial-to-arterial connections are non-access-controlled highways. This research focused exclusively on a freeway-to-arterial interchanges.

There are several basic interchange configurations to accommodate turning movements at a grade separation and it is determined by number of intersection legs, expected volumes of through and turning movements, composition and type of traffic, topography, design control, proper signing, and physical constraints such as existing rivers, railroads, and roadways.

All freeway interchanges with non-access-controlled highways should provide ramps to serve all basic directions to prevent wrong-way movements. According to AASHTO 2004, the term "ramp" includes all types, arrangements, and sizes of turning roadways that connect two or more legs at an interchange. The different ramp patterns of an interchange (i.e. the different types of interchange configurations) are made up of various combinations of ramps. Figure 2.1 illustrates typical interchange configurations: from the simplest full-diamond interchange to complex, multi-level directional interchanges. Many variations of each of these basic interchange configurations are possible.

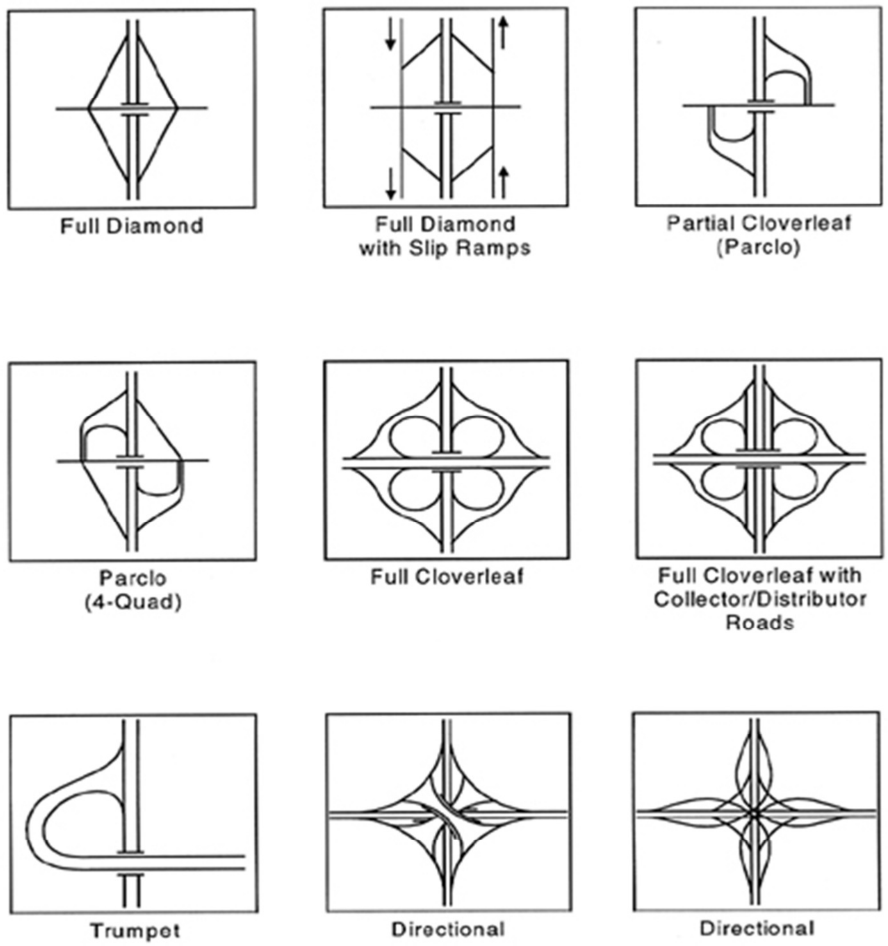

FIGURE 2.1 TYPICAL INTERCHANGE CONFIGURATIONS (BAUER, M. AND HARWOOD, W., 1998)

A one way road that leaves a mainline highway facility is called an off-ramp or exit ramp. A one way road that joins a mainline highway facility is called as an on-ramp or entrance ramp. This distinction is important because according to Cirillo (1967) & Lundy (1966), the accident rate of on-ramps was consistently lower than off-ramp accident rates. Accordingly an on-ramp accident of 0.59 accident per MVMT and off-ramp accident of 0.95 accident per MVTM have been confirmed. Vehicles typically travel along off-ramps at higher speeds than along on-ramps, so that accidents are more likely to occur on off-ramps. Figure 2.2, illustrates a number of typical ramp configurations. Each of the ramps of the ramp configurations illustrated traffic exiting from a mainline freeway, but an analogous ramp configuration for traffic entering the mainline freeway also exists.

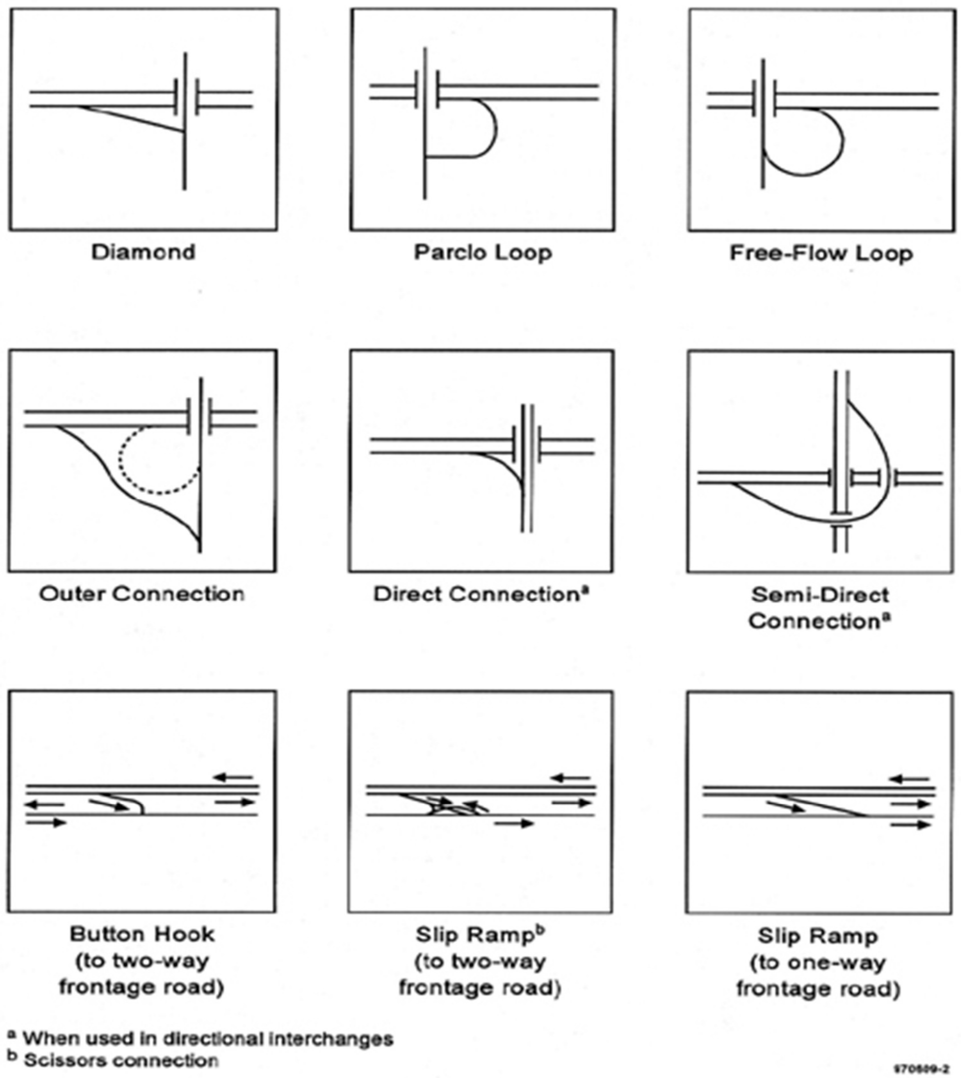

FIGURE 2.2 TYPICAL RAMP CONFIGURATIONS (BAUER, M. AND HARWOOD, W., 1998)

2.5 Background of Safety on Freeway Ramps

Numerous studies have studied the safety performance of freeway ramps during the past several decades. Bared, J., Giering G., Warren, D., (1999) developed the statistical model of accidents to estimate accident frequencies for entire ramps as a function of speed change lane length among other variables. According to the accident model developed in that study, the longer speed change lane showed the less accident frequency.

The result of the study by Lord, D., Bonneson, J., (2005), showed that the exit ramps are more dangerous and the non-free-flow type ramp experience twice as many accidents as other types of ramps. Previous researchers have developed several crash prediction models to relate crash frequency at ramp sections to different explanatory variables such as traffic volumes and ramp design elements.

Bauer, M, Harwood, W. (1998), studied the relationship between traffic crashes and highway geometric design elements and traffic volumes for interchange ramps and speed change lanes. The statistical modeling approaches used in that research included Poisson and negative binomial regression. Several models were developed to predict crashes on ramp sections and speed change lanes. The variables that were included in crash models included mainline freeway AADT, ramp AADT, area type (rural/urban), and ramp type (on/off), ramp configuration, right shoulder width, and lengths of ramp and speed-change lane. The regression model is presented in Section 2.6 of this study.

Accident rates decrease as length of weaving area, or acceleration and deceleration lane increases (Cirillo 1967, 1968, 1970). Cirillo developed statistical model and provided a relationship between the length of weaving

and acceleration and deceleration lanes and traffic volume levels and percentage of merging and diverging traffic. Increase in traffic volume was associated with an increase in crash. The effect of acceleration lane length on accident rate was significant when merging traffic percentage exceeded 6% of the main line traffic volume. As the percentage of merging traffic increase beyond this volume, the additional length of acceleration lane provides a significant reduction in accidents. The effect was not as great for deceleration lanes compared to acceleration lanes.

Studies suggested that a good portion of the accidents associated with ramps occur at the entrance and exit of ramps. Mullins and Keese (1961) found that 23% of all through-lane accidents occur near entrance terminals. 52% of the on-ramp accidents according to Lundy (1966) occur at entrance terminal.

McCartt, A., Northrup, V., Retting, R. (2004) studied about the types and characteristics of ramp-related motor vehicle crashes on urban interstate roadways in Northern Virginia. The study found that 48% accidents occurred in the process of exiting freeway, 36% occurred when the traffic entering and 16% occurred in the midpoint.

2.6 Log-linear Regression Models

Bauer, M. and Harwood, W. (1998) developed statistical model for interchange. These models are Log-linear regression models. They included Poisson and negative binomial regression models. Statistical background on both the Poisson and negative binomial models is provided next.

The following notations are used:

n = interchange elements (e.g., ramp proper segments, entire ramps).

i = is a set of q parameters $(X_{i1}, X_{i2}, \dots, X_{iq})$ (e.g. the geometric design, traffic volume, and other related characteristics of that element.

Y_i= the number of accidents occurring at the i^{th} element during a specific period (say 3-year): where $i = 1,2, \dots, n$.

y_i= the actual observation of y_I during the 3-year period, where $y_i = 0,1,2, \dots$ and $i = 1,2, \dots, n$.

$E(Y_i) = \mu_i$ = the expected number of accidents at the i^{th} element and the q parameters,

Note: In section 2.5 of this study all logarithms are natural logarithms and are denoted by log.

The main objective of a statistical model is to develop a relationship $E(Y_i) = \mu_i$ and q parameters, $X_{i1}, X_{i2}, \dots, X_{iq}$.

This relationship can be formulated through a general linear model (GLM) of the form:

$$\text{Function}\ (\mu_i) = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_q X_{iq} \tag{2.1}$$

where:

β_0 , β_1 , β_2 , ... , β_q, are the regression coefficients and estimated from the data.

The estimation procedure used to obtain the regression coefficients is dependent on the assumption made about the distribution of the Y_I ,

2.6.1 Poisson Regression Model

The assumption of a log-normal distribution [i.e., the assumption that $\log(Y_i)$ follows a normal distribution] is not valid when the average number of accidents at a ramp is small. The Poisson model then becomes a natural choice as it models the occurrence of rare discrete events well. The Poisson distribution has a mean and variance, σ^2 , both equal to μ.

According to the model formulated by Bauer and Harwood (1998):

$$\log(\mu_i) = \beta_0 + \sum_{j=1}^{q} \beta_j X_{ij} \tag{2.2}$$

Assuming the number of accidents, Y_i , follows a Poisson distribution with mean μ, the probability that a ramp with y_i accidents can be expressed as

$$P(Y_i = y_i;\ \mu_i) = \frac{\mu_i^{y_i} e^{-\mu_i}}{y_i!} \tag{2.3}$$

where: $y_i!$ denotes the factorial of y_i.

Maximum likelihood estimation method is used to estimate the Poisson regression coefficients $\beta_0, \beta_1, \ldots, \beta_q$. Maximization of the likelihood function is performed by taking the derivative of the likelihood function with respect to the parameter value. However, it is convenient to take the natural log of the likelihood function before differentiating. Since the natural log is a monotonic function, maximizing the log-likelihood is equivalent to maximizing the likelihood.

So, the likelihood is:

$$L(y_i, \ldots, y_n, \mu) = \prod_{i=1}^{n} f(x_i, \mu) = \frac{e^{-n\mu}\mu^{(y_i+\cdots+y_n)}}{(y_i! \times \ldots \times y_n!)} \tag{2.4}$$

The log-likelihood over all n interchange elements in the category of elements is therefore:

$$log(L) = -n\mu + (y_1 + \cdots + y_n)\log(\mu) - \log(y_1! \times \ldots \times x_n!) \tag{2.5}$$

Which is equivalent to:

$$\log(L) = \sum_{i=1}^{n} [y_i \log(\mu_i) - \mu_i - \log(y_i!)] \tag{2.6}$$

2.6.2 Negative Binomial Regression Model

As it has been discussed in Section 2.5.1, in Poisson distribution the mean and the variance of the distribution are equal. However, previous traffic accident research has shown that this is not always the case.

Paternoster and Brame, (1997); Osgood, (2000) suggested the negative binomial distribution as an alternative to the Poisson when there is evidence of overdisperson.

Overdispersion is a phenomenon that implies there is more variability around the model's fitted values than is consistent with a Poisson formulation. Suppose a Poisson model is used for modeling accidents and if the variance (or dispersion) of the data exceeds the estimated mean of the accident data distribution, then the data are said to be overdispersed, and the underlying assumption of the variance being equal to the mean for the Poisson distribution is violated (Bauer, M. and Harwood, W. (1998)). The negative binomial is proposed as a means to correct for this problem (Osgood, 2000). Negative binomial distribution has two parameters, unlike the Poisson distribution.

For negative binomial distribution the relationship between the expected number of accidents occurring at the i^{th} element and the q parameters is same as Equation (2.1). The probability that a ramp $\mathrm{Y_i} = \mathrm{y_i}$ accidents can be expressed as:

$$P(Y_i = y_i) = \frac{\Gamma\left(y + \frac{1}{k}\right)}{\Gamma(y+1)\Gamma\left(\frac{1}{k}\right)} \frac{(k\mu)^y}{(1+k\mu)^{y+\frac{1}{k}}} \; ; \; y_i = 0,1,2,\ldots \tag{2.7}$$

The mean and variance of the negative binomial distribution of accident frequency are given by:

$$\mathrm{Mean} = \mathrm{E(Y)} = \mathrm{\mu_i} \tag{2.8}$$

$$\mathrm{Variance} = \mathrm{Var(Y)} = \mathrm{\mu_i} + \mathrm{k}\mu^2 \tag{2.9}$$

where:

$k =$ the negative binomial dispersion parameter

The model regression coefficients $\beta_0, \beta_1, \ldots, \beta_q$, are estimated by the method of maximum likelihood minimizing the negative of the log likelihood.

Bauer, M. and Harwood, W (1998) developed the log likelihood for the negative binomial distribution and is given by:

$$\log(\mathrm{L}) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{y_i} \log\left[\frac{\alpha}{(\alpha + 1)}\right] - \mathrm{nk}\log(\mathrm{a} + \alpha) + \text{function of } \mathrm{y_i}, \mathrm{k} \qquad (2.10)$$

Modifying Equation (2.10):

$$\log(\mathrm{L}) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{y_i} \log\left[\frac{\mu\mathrm{k}}{(\mu\mathrm{k} + 1)}\right] - \frac{n}{k} \log(\mathrm{a} + \mu\mathrm{k}) + \text{function of } \mathrm{y_i}, \mathrm{k} \qquad (2.11)$$

Which is equivalent to:

$$\log\left(\frac{\mu_{\mathrm{i}}}{\left(\mu_{\mathrm{i}} + \frac{1}{k}\right)}\right) = \beta_0 + \beta_1 \mathrm{X_{i1}} + \beta_2 \mathrm{X_{i2}} + \cdots + \beta_{\mathrm{q}} \mathrm{X_{iq}} \qquad (2.12)$$

2.6.3 Goodness of Fit Measure

The scaled deviance and Pearson’s chi-square statistic are helpful in assessing the goodness of fit of a given generalized linear model. According to Nelder and Wedderburn (1972), for a fixed value of the dispersion parameter ϕ, scaled deviance is defined to be twice the difference between the maximum achievable log likelihood and the log likelihood at the maximum likelihood estimates of the regression parameters.

Let $l(x,\mu)$ the log-likelihood function,

where:

μ = the mean of the distribution

y = the response values,

Then the scaled deviance is defined by:

$$SD(y,\mu) = 2l\big(l(y,y) - l(y,\mu)\big) \tag{2.13}$$

$$SD(y,\mu) = \frac{D(y,\mu)}{\phi} \tag{2.14}$$

where:

$D(y,\mu)$ =model (residual) deviance

ϕ= the generalized linear model dispersion parameter

Accordingly, scaled deviance for the Poisson distribution is given by Equation (2.15):

$$\mathrm{D} = 2\left[\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{y_i} \ln\left(\frac{\mathrm{y_i}}{\mathrm{\mu_i}}\right) - \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{y_i} - \mathrm{\mu_i})\right] \tag{2.15}$$

Also, scaled deviance for the negative binomial distribution is given as:

$$D = 2\sum_{i=1}^{n}\left[y_i log\left(\frac{y_i}{\mu_i}\right) - \left(y_i + \frac{1}{\kappa_i}\right) log\left(\frac{y_i + \frac{1}{k_i}}{\mu_i + \frac{1}{\kappa_i}}\right)\right] \tag{2.16}$$

where:

$k =$ the negative binomial dispersion parameter

Since ϕ is one for both Poisson distribution and negative binomial distributions the scaled deviance is equal to the deviance.

Pearson's chi-square statistics is given by:

$$\chi^2 = \sum_{i=1}^{n}\frac{(y_i - \mu_i)^2}{V(y_i)} \tag{2.17}$$

and the scaled Pearson's chi-square is defined as:

$$\frac{\chi^2}{\phi} \tag{2.18}$$

where:

$\mu =$ the mean of y

$V(y_i) =$ the variance function of the distribution.

In both Equation (2.16) and (2.17) the weight to each interchange is to be one.

Since ϕ is one for both Poisson distribution and negative binomial distributions the scaled Pearson's chi-square is equal to the Pearson's chi-square statistics.

2.7 Traffic Crash Prediction Model

Bauer, M. and Harwood, W. (1998) developed models to predict accidents. Initially accidents on ramps and speed-change lanes were modeled separately with the thought that accident predictions from the separate models could be added together to determine the combined safety performance of a ramp and its adjacent speed-change lane. The study proved that the separate models, by themselves, didn't provide an adequate fit to the data. Therefore, they developed the best models of the safety performance of interchange ramps and speed-change lanes by combining the accident experience of ramps and their adjacent speed-change lanes into a single model.

Independent variables included in the model include:

- Ramp AADT
- Mainline freeway AADT
- Area type (rural/urban)
- Ramp type (off/on)
- Ramp configuration
- Length of speed-change lane
- Ramp length

It was determined that these seven independent variables are all statistically significant at the 20-percent significance level in the model for total accidents, and all of these independent variables, except ramp configuration, are significant in the model for fatal and injury accidents.

To predict the average accident frequency for a ramp including the adjacent speed-change lane, the regression coefficients $\beta_0, \beta_1, \beta_{2,...,}\beta_q$ are replaced in equation (2.19) by the estimated values of the coefficients and the variables $X_{1,}X_2, \dots, X_q$ are replaced by their appropriate values or levels.

$$function(\mu_i) = exp(\beta_0)\left(AADT_{ramp}\right)^{\beta_1} exp(\beta_2 X_{i2}) \cdot \dots \cdot exp\left(\beta_q X_{iq}\right) \qquad (2.19)$$

For example, the expected 3-year total accident frequency can be estimated as

$$\begin{aligned} Y = e^{-7.27}(X_1)^{0.78}(X_2)^{0.13} exp(0.45X_3) exp(0.78X_4) exp(-0.02X_5) \\ exp(0.69X_6) exp(-0.37X_7) exp(0.37X_8) \\ exp(-2.59X_9) exp(1.62X_{10}) \end{aligned} \qquad (2.20)$$

where:

Y = expected number of total accidents in a 3-year period on entire ramp plus adjacent speed-change lane

X_1 = ramp AADT (veh/day)

X_2 =mainline freeway AADT for the direction of travel in which the ramp is located (veh/day)

X_3 = 1 if the ramp is a diamond ramp; 0 otherwise

X_4 = 1 if the ramp is a parclo loop ramp; 0 otherwise

X_5 = 1 if the ramp is a free-flow loop ramp; 0 otherwise

X_6 = 1 if the ramp is an outer connection ramp; 0 otherwise

X_7 = 1 if the area type is rural; 0 otherwise

X_8 = 1 if the ramp is an off-ramp; 0 otherwise

X_9 = speed-change lane length (mi)

X_{10} = ramp length (mi)

The estimate of dispersion after fitting, as measured by the deviance and Pearson's chi-square divided by the degrees of freedom, are 1.0 and 0.95 respectively for total accidents which are well within the acceptable range. Also the R^2 goodness of fit is approximately 0.38.

Among these variables, it was found that mainline and ramp AADT to be the most important predictor of accident on ramps. The increase in crash frequency was associated with higher accidents. The effect of acceleration length was more complicated since on one hand longer lengths provide safer traffic maneuvering and on the other hand corresponding increased length may provide longer exposure and more accidents.

It was noted that the 3-year accident prediction models were divided by 3 to obtain the corresponding accidents per ramp per year.

2.8 Empirical Bayes Technique

Bayes theorem is a probability theory that shows how new information can be used to update or revise an existing set of probability. The prior probability may have to be estimated based on very little information. These probabilities would be improved as more information becomes available.

When it comes to traffic safety, Empirical Bayes (EB) is a theoretical framework that combines the actual crash count of a location with an estimated crash frequency determined from the safety performance function of the same location. Sayed (1995) stated that the expected number of accidents at a location is a random variable that fluctuates around some unknown mean. This randomness is reason that historical accident data at a location does not always accurately reflect its long-term accident characteristics. Higle and Witkowski, (1988) stated that a location that has low accident frequency during long periods of time may have had high accident rates during portions of this period and vice versa and confirmed that Empirical Bayes approach accounts for random variations of accident rate.

The technique is based on Bayes' theorem which can be mathematically described as:

$$P(\phi|x) = \frac{P(x|\phi) \times P(\phi)}{\sum P(x|\phi) \times P(\phi)} \tag{2.21}$$

Where:

ϕ = a parameter such as the number of accidents at a location,

$P(\phi)$ = the prior distribution of ϕ,

$P(x|\phi)$ = the probability of making x observation for a specific value of ϕ (observation distribution), and

$P(\phi|x)$ = the posterior distribution of ϕ which represents the resolution of the prior distribution given the observations.

According to Calvin (1990) the distribution of the observation is assumed to be a Poisson or Binomial distribution and the prior distribution will be a gamma or beta distribution. In the Empirical Bayes approach, the parameters are estimated using a sample of observations from population of similar locations.

2.8.1 Empirical Bayes Safety Estimate

Hauer (1992), Brude and Larsson (1988) stated that the safety of a location provide clues about its traffic and road characteristics, and its historical accident data. The Empirical Bayes (EB) approach makes use of both kinds of clues and is used to refine the estimate of the expected number of accidents at a location by combining the observed number of accidents at the location with the predicted number of accidents obtained from the GLM model to yield a more accurate, location-specific safety estimated. Equation 2.31 confirmed this. Brude and Larsson, (1988) showed that EB method significantly reduces the regression to the mean effects that are inherent in observed accidents count. Regression to the mean is a statistical phenomenon that refers to the tendency of extreme events (high number of

accidents) to be followed by less extreme values (a lower number of accidents) even if no treatment is applied to the field configuration that generates the accidents at that location.

According to Hauer (1992), the EB safety estimate can be calculates by.

$$EB_{safety\ estimate} = \alpha.pred + (1-\alpha).count, \qquad (2.22)$$

where,

$$\alpha = \frac{1}{1 + \frac{var(pred)}{pred}}$$

where,

count = observed number of accidents at the location

pred = predicted number of accidents as estimated from the GLIM model

var(pred) = the variance of the GLM estimates

According to (Sayed et.al., 1998),

$$var(pred) = \frac{(pred)^2}{\kappa}$$

Where:

$\kappa =$ shape parameter

Then, Equation (2.22) can be rearranged as:

$$EB_{safety\ estimate} = \left(\frac{\kappa}{\kappa + pred}\right) pred + \left(\frac{pred}{\kappa + pred}\right) count \qquad (2.23)$$

In addition, the variance of the EB estimate can be calculated using (Kulmala, 1995):

$$var\left(EB_{safety\ estimate}\right) = \frac{\kappa\, pred^2}{(\kappa + pred)^2} + \left(\frac{pred}{\kappa + pred}\right)^2 count \qquad (2.24)$$

2.8.2 Bayesian Identification of Accident-Prone Locations

Higle and Witkowski (1988) described that Empirical Bayes procedure is a useful technique to identify accident-prone locations.

The following notations are used:

$\tilde{\lambda}_i$ = accident rate at a location i (treated as a random variable),

N_i = number of accidents at location i during the period of time in question,

V_i = number of vehicles passing through location i during the period of time in question,

$f_i\ (\lambda | N_i, V_i)$ = probability density function associated with the accident rate at location i given the observations N_i and V_i (Posterior distribution) ,

$f_R\,(\lambda) =$ probability density function associated with the accident rate across the region (Posterior distribution) ,and

α, β = parameters of gamma distribution.

Two assumptions were made:

1. At any given location, the actual number of accidents (N_i) follows a Poisson distribution such that at any given location, where the accident rate is known $(\tilde{\lambda}_i = \lambda)$ and the expected value is given by λV_i then the observation probability distribution is given by the following:

$$P\left[N_i \;= n|\tilde{\lambda}_i = \lambda, V_i\right] = \frac{(\lambda V_i)^n}{n!}\; e^{-\lambda V_i} \tag{2.25}$$

2. The probability distribution of the regional accident rate (the prior distribution), $f_R(\lambda)$, follows a gamma distribution and is given by:

$$f_R(\lambda) = \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda} \tag{2.26}$$

The parameters α and β of the prior distribution are estimated using the method of moments estimates (MME), and are chosen so that the mean and variance associated with the gamma distribution are equal to the mean $(\overline{x})$ and variance (s^2) of the sample.

If $(\overline{x})$ and (s^2) are the sample mean and variance of the observed accident rates respectively, and m is the number of locations under observations, then:

$$\overline{x} = \frac{1}{m}\sum_{i=1}^{m}\frac{N_i}{V_i} \tag{2.27}$$

$$s^2 = \frac{1}{m-1}\sum_{i=1}^{m}\left(\frac{N_i}{V_i} - \overline{x}\right)^2 \tag{2.28}$$

Morris (1988) and Berger (1985) modified the parameters of gamma distribution to avoid the bias and improve the estimation. Accordingly, the probability density function associated with the accident rate at a location i is given by:

$$f_1(\lambda|N_i, V_i) = \frac{{\beta_i}^{\alpha_i}}{\Gamma(\alpha_i)}\lambda^{\alpha_i - 1}e^{-\beta_i\lambda} \tag{2.29}$$

And thus, location i will be identified as accident-prone if there is a significant probability that the location's accident rate, $\overline{\lambda}_i$, exceeds the observed regional accident rate, X_R.

Thus, location i is identified as accident prone if:

$$P\{\overline{\lambda}_i > X_R | N_i, V_i\} > \delta \tag{2.30}$$

or equivalently if:

$$\left[1 - \int_0^{X_R} \frac{{\beta_i}^{\alpha_i}}{\Gamma(\alpha_i)} \lambda^{\alpha_i - 1} e^{-\beta_i \lambda}\, d\lambda\right] > \delta \tag{2.31}$$

where:

$\delta =$ the confidence level desired, such as 0.95 or 0.99, and

The value of the regional accident rate, X_R, is calculated using:

$$X_R \;=\; \frac{\sum_{i-1}^{m} N_i}{\sum_{i-1}^{m} V_i} \tag{2.32}$$

Sayed (1995) modified the Higle and Witkowski's method by substituting $\alpha + \lambda_{c_i} V_i$ for α_i in Equation (2.31) and is given by:

$$\left[1 - \int_0^{X_R} \frac{{\beta_i}^{\left(\alpha + \lambda_{c_i} V_i\right)}}{\Gamma\left(\alpha + \lambda_{c_i} V_i\right)}\, \lambda^{\left(\alpha + \lambda_{c_i} V_i - 1\right)} e^{(-\beta_i \lambda)}\, d\lambda\right] = \delta \tag{2.33}$$

2.9 Simulation Modeling

2.9.1 Choice of a Simulation Tool

A need for simulation modeling has been increasing to understand the behavior of traffic as transportation systems have become more complex. Many researches in the past have studied different similarities and differences of simulation tools and their capacity to model different combinations of traffic, highway type, geometric configuration, etc. of the system.

Gettman D., and Head L., (2003) conducted a study to evaluate the various simulation models' capabilities for producing measures of intersection safety and specify algorithms for calculating the measures. The nine multipurpose micro simulation software includes CORSIM, SIMTRAFFIC, VISSIM, HUTSIM, PARAMICS, TEXAS, AIMSUN, WATSIM, and INTEGRATION. It was noted that VISSIM, AIMSUN, PARAMICS, and TEXAS outputs the proper TRJ files required by SSAM. It was concluded that there are a number of advantages that VISSIM possesses over other micro-simulation tools. VISSIM appears to be a full-featured microscopic simulation model with the ability to obtain detailed state variable information on each vehicle on time scales with better than second-by-second accuracy. Moreover it has been interfaced to other external codes such as hardware signal controllers, thus the developers have experience in development collaboration. The priority rules feature of VISSIM appears to allow complex modeling of junction behavior, including friendly merging (situations where following vehicles will slow for merging vehicles to create a gap), as it occurs in the real world. It is not apparent that other simulation models are able to represent such behavior. VISSIM allows multilane merging behavior; it is typical for vehicles entering the mainline flow to cross the path of an oncoming vehicle traveling

in the same direction as the intended direction of travel of the entering vehicle and start accelerating in the adjacent lane. In this way, the oncoming vehicle can continue at its current speed without having to break for the turning vehicle. VISSIM appears to support most of the modeling features required for obtaining surrogate measures at a reasonable level of fidelity.

Because of its competitive advantages, combined with its capability to analyze networks of all sizes, VISSIM was chosen to perform the simulation modeling of traffic.

2.9.2 VISSIM Micro-Simulation Tool

According to VISSM User Manual (2009), VISSIM is a microscopic, time step and behavior-based simulation model developed to model urban traffic and public transport operations. The program can analyze private and public transport operations under constraints such as lane configuration, traffic composition, traffic signals, etc., thus making it a useful tool for the evaluation of various alternatives based on transportation engineering and planning measures of effectiveness.

The model was developed at the University of Karlsruhe, Germany during the early 1979. PTV America, Inc., a subsidiary of PTV AG located in Karlsruhe, Germany, is the North American distributor and developer of PTV Vision software products. VISSIM version 5.20 was used in this study.

Unlike many other simulation tools, it is not strictly node-link based, it is based on link-connector geometry. In VISSIM the user builds a network based on

aerial photographs at the exact point where they are needed to have the desired effect on road-users.

Traffic flow in VISSIM is simulated by moving driver-vehicle-units through a network. Every driver is stochastically assigned to a specific vehicle. Consequently, the driver's behavior will be adapted to the vehicle performance characteristics. Attributes characterizing each driver-vehicle-unit can be classified in to three components: (1) technical specification of the vehicle (e.g. length, engine power, weight, maximum speed, potential acceleration actual position in the network, and actual speed and acceleration), (2) behavior of driver-vehicle units (e.g acceleration based on current speed and driver's desired speed, (3) interdependence of driver-vehicle units (e.g. reference to leading and following vehicles on own and adjacent travel lanes)

2.10 SSAM Conflict Analysis Tool

The Surrogate Safety Assessment Model (SSAM) is owned by FHWA. According to Lili Pu and Rahul Joshi (2008), SSAM operates by processing data describing the trajectories of vehicles driving through a traffic facility and identifying conflicts. The vehicle trajectory input data for SSAM are generated by traffic simulation software in a trajectory file format (where files are labeled with a .trj file extension), specially designed for SSAM. SSAM calculates surrogate measures of safety corresponding to each vehicle-to-vehicle interaction and determines whether or not each interaction satisfies the criteria to be deemed an official conflict. A table of all identified conflicts and their corresponding surrogate safety measures is then presented to the user.

Figure 2.3 illustrates the workflow for using SSAM. It was reported that the users of the SSAM software would include traffic safety engineers, traffic simulation analysts, and traffic researchers.

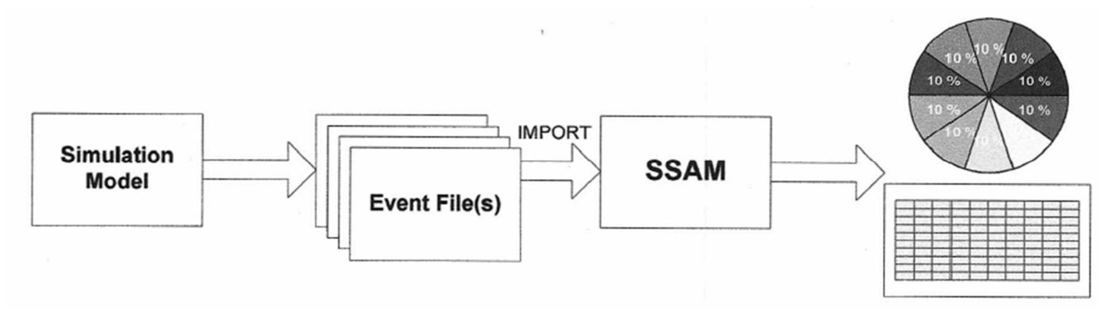

FIGURE 2.3 EVENT-FILE BASED INFORMATION FLOW DIAGRAM (Gettman D., and Head L., (2003)).

Surrogate Safety Assessment (SSAM) software uses two threshold values for surrogate measures of safety to delineate which vehicle-to-vehicle interactions are identified as conflicts. These two thresholds are Time-to-Collision (TTC) and Post-Encroachment Time (PET). SSAM utilizes a default maximum TTC value of 1.5 seconds as suggested by (Sayed, Brown, Navis, 1994) and (Hayward, 1972) and the maximum PET value of 5 seconds as suggested by Hyden (1987).SSAM filters out conflicts that do not fall in the specified ranges. These default values were used in this study.

Gettman, Pu, Sayed, and Shelby (2008) developed conflict identification algorithm of SSAM and described as follows:

First, SSAM determines the dimensions of the analysis area based on the TRJ file and constructs a zone grid to cover the entire rectangular analysis area. By dividing the region into zones, the number of vehicle-to-vehicle comparisons necessary to identify potential conflicts is reduced considerably.

Second, SSAM analyzes a single time step of a trajectory file. For each vehicle in the analysis region, it projects that vehicle's expected location as a function of its current speed, if it were to continue traveling along its (future) path for up to the duration of the configured time-to-collision (TTC) value.

Third, for each vehicle, SSAM calculates the rectangular perimeter delineating the location and orientation of that vehicle at its projected future position. Any time a vehicle is added into a zone that currently contains one or more other vehicles, SSAM checks for overlap of the new vehicle (rectangle) with each of the other vehicles (rectangles) in that zone. It is possible that two vehicles may partially occupy the same zone without overlapping. However, two overlapping rectangles indicate that a future collision is projected for this pair of vehicles, and therefore, a potential conflict has been identified. SSAM maintains a list of all conflicting vehicle pairs (all conflict events) for the current time-step. Each time-step, the list is prepopulated with all conflicting vehicle-pairs from the prior time-step. If the current vehicle being added to the zone grid overlaps with any other vehicle, that vehicle-pair is added to the conflict list for the current time-step (if not already in the list).

Four, SSAM continues to perform a more detailed processing of each conflicting vehicle-pair in the list for the current time-step as follows:

(a) The TTC of the vehicle-pair is updated by iteratively shortening the future projection timeline by a tenth of second and re-projecting both vehicles as before over successively short distances until the pair of vehicles no longer overlaps in their projected locations. In this way, a more accurate TTC value is established for this time-step. Instead of the large overlap, the vehicles can have just barely come into contact. Note that if the projection timeline reduces to zero seconds and the vehicles still overlap, then this is a crash.

(b) The minimum TTC (taking the minimum of the current TTC value and that of the prior time-step, if applicable) are calculated and updated. Also, the current (actual) positions of both vehicles are recorded for post-encroachment analysis.

(c) If it was found that the vehicle-pair does not overlap over any projection time between zero and maximum TTC, then this vehicle-pair has made its way into the conflict event list by virtue of being in the list during the prior time-step. In this case, the event remains in the list, watching for the one vehicle (the trailing vehicle) to eventually occupy (or encroach on) on a position formerly held by the other vehicle (the leading vehicle). The time differential between when the leading vehicle occupied this location and the trailing vehicle arrived is the post-encroachment time (PET). If a post-encroachment was observed, then the minimum PET is updated, and this conflict event remains in the list, as the post-encroachment could potentially reduce as the vehicle trajectories progress over time.

(d) If a vehicle-pair in the conflict event list is no longer on an imminent collision course, and it is clear that PET to any prior positions could not further reduce the minimum PET, or the maximum PET has elapsed, then this vehicle-pair is identified for removal from the conflict event list. Prior to removal, all final surrogate measures are computed, including conflict starting and end points, and conflict angles.

After SSAM identifies the conflicts, it classifies them in to four types: rear end, lane change, crossing and unclassified conflicts. The link and lane information is utilized for classification in the case that the vehicles both occupy the same link at either the start or end of the conflict event. The simulation model (VISSIM) that produced the vehicle trajectory data can generally provide link and lane information for both vehicles. If both vehicles occupy the same lane at the start and end of the event, then it is classified as a rear-end event. If either vehicle ends the conflict event in a different lane than it started (while having not changed links), then the event is classified as a lane change. If either of the vehicles changes links over the course of the event, then the conflict angle determines the classification using the threshold values mentioned next.

The event type is classified based on the absolute value of the Conflict Angle. A conflict is classified as unclassified if the conflict angle is unknown, rear-end if ||Conflict Angle|| < 30°, crossing if ||Conflict Angle|| > 85°, lane change if 30° ≤ || conflict angle || ≤ 85°. Figure 2.4 illustrates the conflict angle. The threshold angles (30° and 85°) were determined by experimentation.

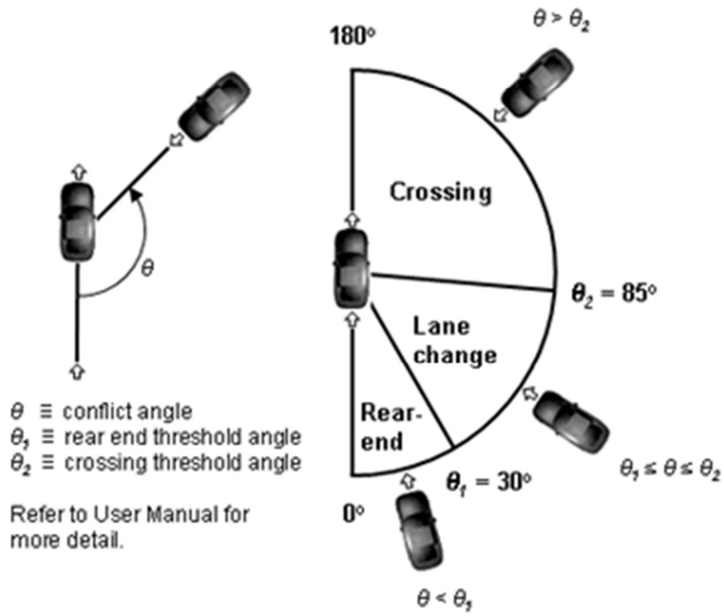

FIGURE 2.4 : ILLUSTRATION OF CONFLICT ANGLE DIAGRAM (SSAM SOFTWARE)

2.11 SAS/STAT Software and the GENMOD Procedure

According to the SAS/STAT software user manual (2011), the software provides comprehensive statistical tools for a wide range of statistical analyses, including analysis of variance, categorical data analysis, cluster analysis, multiple imputation, multivariate analysis, nonparametric analysis, power and sample size computations, psychometric analysis, regression,

survey data analysis, and survival analysis. A few examples include nonlinear mixed models, generalized linear models, correspondence analysis, and robust regression. The current release of SAS software, SAS 9.3 version, was used for this study.

A component of SAS software called GENMOD procedure was used. The GENMOD procedure fits generalized linear models, as defined by Nelder and Wedderburn (1972). The class of generalized linear models is an extension of traditional linear models that allows the mean of a population to depend on a linear predictor through a nonlinear link function and allows the response probability distribution to be any member of an exponential family of distributions. Many widely used statistical models are generalized linear models. These include classical linear models with normal errors, logistic and probit models for binary data, and log-linear models for multinomial data. Many other useful statistical models can be formulated as generalized linear models by the selection of an appropriate link function and response probability distribution.

The GENMOD procedure fits a generalized linear model to the data by maximum likelihood estimation of the parameter vector. There is, in general, no closed form solution for the maximum likelihood estimates of the parameters. The GENMOD procedure estimates the parameters of the model numerically through an iterative fitting process. The dispersion parameter is also estimated by maximum likelihood or, optionally, by the residual deviance or by Pearson's chi-square divided by the degrees of freedom. Covariances, standard errors, and p-values are computed for the estimated parameters based on the maximum likelihood estimators.

3. Research Approach and Methodology

3.1 Field Validation

The field validation effort for the study sites were assessed with SSAM, and the results were compared to actual crash histories. Also, surrogate safety estimates were compared with traditional volume-based models for crash prediction. The field validation testing was based solely on modeling with the VISSIM simulation.

3.2 Purpose

The main purpose of the field validation effort was to compare the predictive safety performance capabilities of the SSAM approach with actual crash experience of merging and diverging freeway sections. This effort consisted of a series of statistical tests to assess the correlation between actual crash frequencies at a series of merge/diverge sections and the corresponding frequency of conflicts observed in simulation models of these sections. Traditional volume-based crash prediction models were used as a basis for comparison.

3.3 Data Assembly and Geometric Definition

Merging and diverging influence areas along freeways at interchanges were selected based on the following guidelines: (1) a sufficient number of

interchanges were needed to obtain the range of parameters necessary to test the methodology, and to establish statistical measure of significance. (2) interchanges were not selected based on their crash performance (e.g., most dangerous interchanges in an area) as this will lead to the regression-to-the-mean bias (Hauer, E. 1980). The regression-to-the-mean bias is the tendency of a randomly high accident frequency occurring at a location during a specific time period to be followed by a smaller accident frequency during a consecutive period of equal duration, even if no treatment is applied to the field configuration that generates the accidents at that location.

Appendix A provided a summary of the twenty-one interchanges used in this study. It shows, for each interchange: the highway names, cross street names, truck percentage, average daily traffic (ADT) and peak hour volume (PHV) for the mainline, on-ramp and off-ramp movements.

Prior to fitting the model all merge/diverge related accidents were isolated from the CDOT accident database. This eliminated the influence of non-merge/diverge accidents from the analysis. Appendix C presents the crash data in terms of average yearly crash counts for each merge/diverge locations. The crash counts were derived by filtering through all interchange crash records to include only two (or more) vehicle crashes. Thus, single-vehicle crashes, such as run-off-road crashes, fixed-object crashes, and animal, pedestrian, or bicycle related crashes, were excluded.

In addition to the crash count, properly defining the interchange geometry was an important part of the modeling process. Traffic exiting a highway is required to reduce the speed. The speed-change lane that enables the driver

to reduce the speed between the highway and the turning roadway in a safe and comfortable manner is called deceleration lane. On the other hand traffic entering a highway is required to increase the speed. The speed-change lane that enables the driver to increase the speed between the highway and the turning roadway in a safe and comfortable manner is called acceleration lane.

Roess and Ulerio (1993) studied the on-ramp and off-ramp junctions and showed that lane changing and turbulence extend to 1500 feet downstream from the tip of the merge gore and 1500 feet upstream from the tip of the diverge gore. Moreover, the mainline traffic starts to change lane upstream of the gore at merge. Similarly at diverging location it is common to see some traffic to change lanes downstream of the gore for adjustment. As a result of these, at both merge/diverge locations crashes at a distance of 1500ft on either sides of the gore (total 3000ft) were compared with the corresponding conflicts recorded for the same distance (3000ft). Figure 3.1 and Figure 3.2 illustrates the model geometric configuration of merge and diverge influence areas respectively. Collection of traffic counts from CDOT crash database and conflict analysis by SSAM were based on the definition of these Figures. The model considered only right-hand traffic flow conditions for both merge/diverge influence areas.

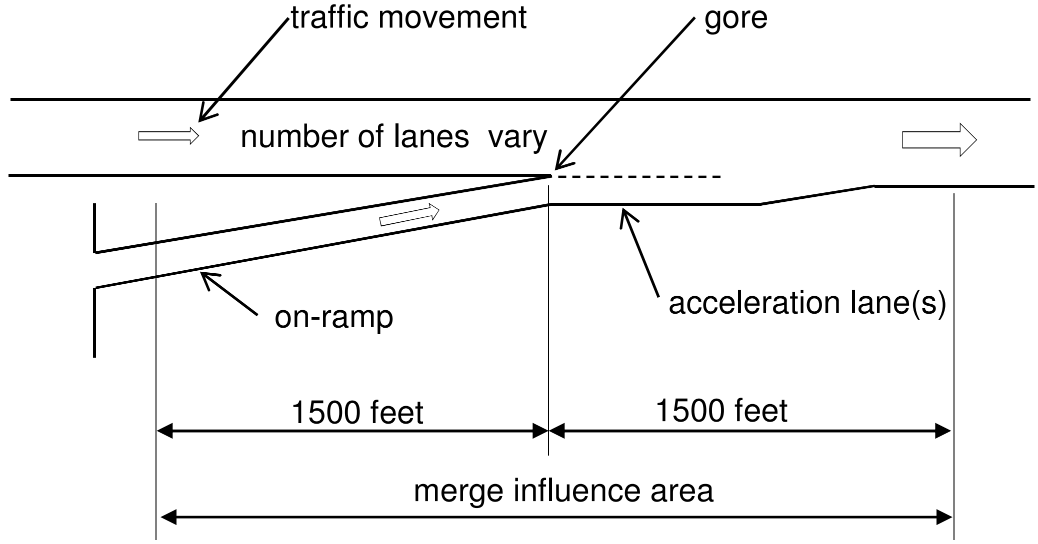

FIGURE 3.1 ILLUSTRATION OF MERGE INFLUENCE AREA

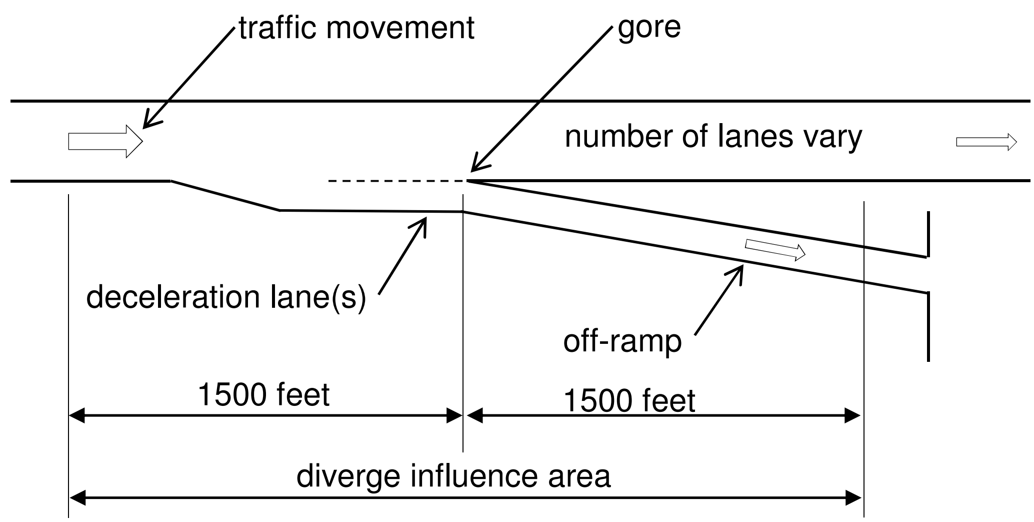

FIGURE 3.2 ILLUSTRATION OF DIVERGE INFLUENCE AREA

3.4 Simulation Modeling of Interchanges and Modeling Assumptions

Forty two merging and diverging locations were coded in VISSIM simulation modeling tool. The process of modeling of interchanges in VISSIM was started by tracing an aerial photo of the proper geometric configuration by defining the number, width, and length of lanes. After the geometric configuration of the interchange was defined, other modeling parameters such as traffic flow (peak-hour volume), traffic composition, percent truck, routing decision, etc., were allocated.

Several modeling parameters were defined during the process including: speed profiles, vehicle type, traffic composition, routing decisions and other aspects. The traffic composition was assumed to be composed of passenger cars and trucks. The percentage of trucks was coded at each interchange. The desired speed profiles were assumed to range from 50mph to 75mph for mainline traffic and 30mph to 45mph for on-ramp and off-ramp traffic. Car-following and lane-changing behavior were set to model freeway (free lane selection) traffic flow using the Wiedemann 99 model with all default parameters used (VISSIM 5.2 User Manual, 2009). A simulation resolution of 5 time steps per simulation second was used. Among the different types of routing decisions a “static” routing option was used which defines the vehicles routes from a start point to any of the defined destinations using a static percentage for each destination.

The lane-changing algorithm in VISSIM allows for two types of lane changes: necessary lane changing and free lane changing. A free lane changing option was chosen. In a free lane change, VISSIM checks for the desired speed

safety distance of the trailing vehicle on the new lane. This safety distance depends on the vehicle speeds.

Following nominal verification, each interchange was simulated five times for a period of 3600 simulation seconds (1 hour). Instead of running multiple simulation runs with different random seeds, a multirun option was used. This option lets VISSIM automatically run the requested five successive runs at each location. When run this way, VISSIM automatically uses a new random seed number at the starts of each run.

The modeled interchanges were tested for realistic and reasonable vehicle behaviors. The TRJ output files from VISSIM run model were imported into the SSAM application to identify traffic conflicts and calculate the corresponding surrogate safety measures. The output from SSAM was formatted and analyzed by SAS GENMOD statistical software to produce safety performance functions.

The traffic flow inputs to VISSIM were based on peak hour volumes, as recorded by the CDOT traffic database. The volumes used for simulation are included in Appendix A.1. Figure 3.3 and Figure 3.4 are screen captures of geometric layout and flow of traffic modeled in VISSIM respectively.

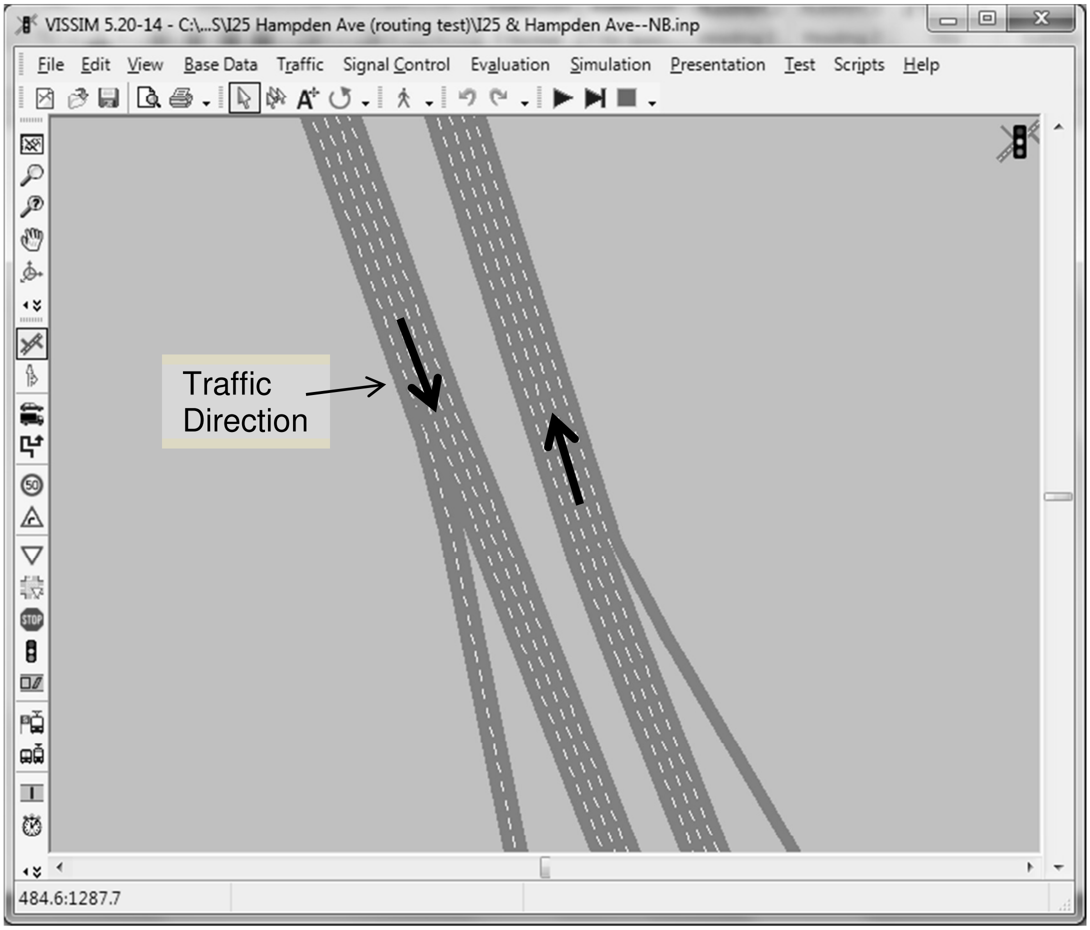

FIGURE 3.3 SCREEN CAPTURE. VISSIM GEOMETRIC MODEL OF I-25 & E HAMPDEN AVE

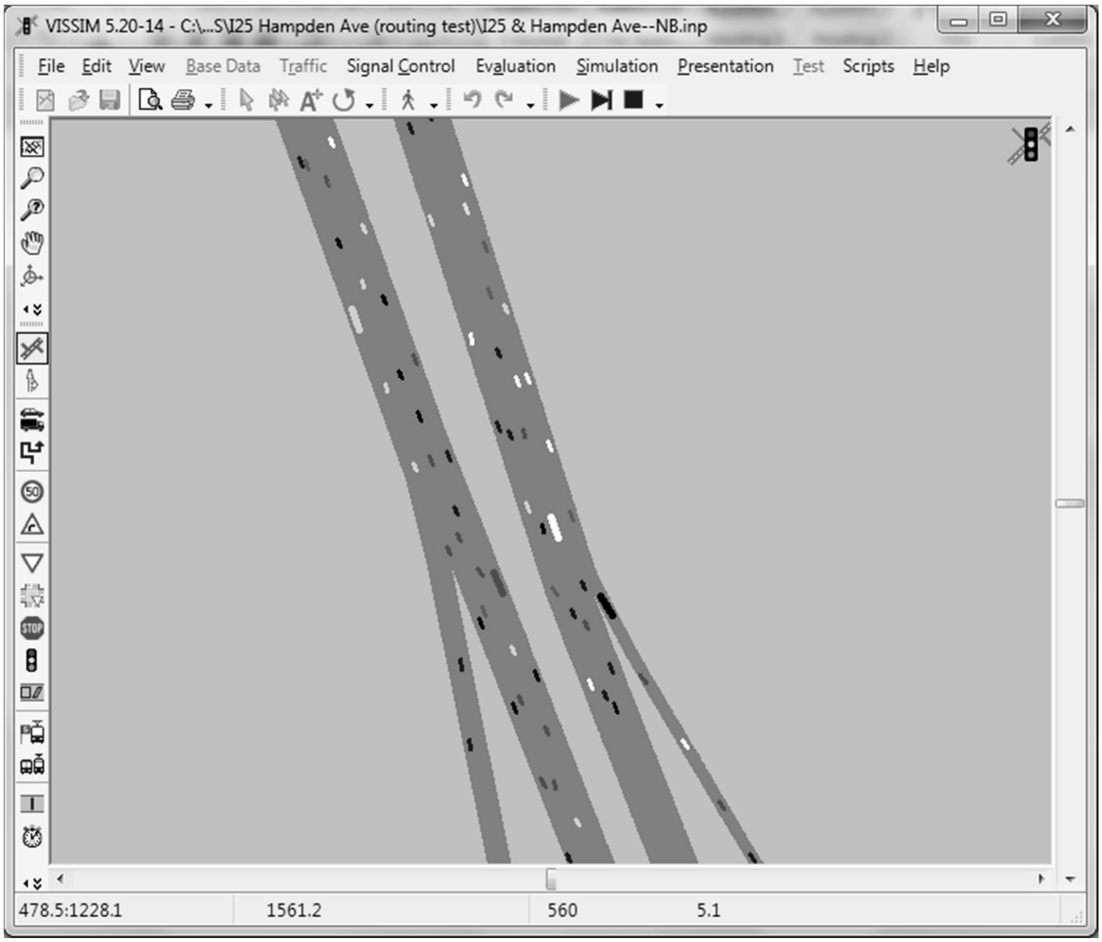

FIGURE 3.4 SCREEN CAPTURE. VISSIM TRAFFIC MODEL OF I-25 & E HAMPDEN AVE

3.5 Identification and Removal of Outliers

Before any statistical inferences were applied, the outliers were identified and removed from the dataset. Outliers are observations or subsets of observations which appear to be inconsistent with the remainder of the data (Barnett & Lewis, 1978). There are three ways for outliers to arise in a sample (Barnett and Lewis (1994, pp. 33-34)): (1) data due to a reading error, a recording error, or a calculation error in the data; (2) a data value that incorrectly included in the data set; (3) a correctly recorded data value that belongs in the data set. Since these causes of outliers are possible to occur in the data, due attention were given to identify and remove them.

The Standardized Residual Criterion (z-score method) was used to identify outliers. The standardized residual, the STUDENT statistic, is the residual expressed in units of standard deviation from the mean value. Thus, a standardized residual with an absolute value of 3 is 3 standard deviations above the mean value. Observations with standardized residual with an absolute value of 3 or greater are potential outliers and were removed from the analysis.

$$Z = \frac{x_i - \bar{x}}{\sigma} \tag{3.1}$$

where: Z= It denotes the number of standard deviations a data value x_i is from the mean, $\bar{x}$.

3.6 Methodology

The methodology used for the field validation task was based on relating surrogate safety measures that SSAM derived from simulation models with actual crash occurrence observed on the field at merging and diverging locations. The field validation effort involve the analysis of 21 interchanges (42 merging and 42 diverging) locations, modeled with the VISSIM simulation.

Gettman, Pu, Sayed, and Shelby (2008) provided five statistical field validation tests for the analysis of intersections. These tests were modified and used in this study for merging and diverging locations:

1. Field Validation Test 1: Merging and Diverging Section Ranking by Total Incidents
2. Field Validation Test 2: Merging and Diverging Section Ranking by Specific Incident Types
3. Field Validation Test 3: Crash and Conflict Prediction Regression Model Paired Comparison
4. Field Validation Test 4: Crash and Conflict Prediction Regression Model Comparative Analysis of Total Incidents
5. Field Validation Test 5: Crash and Conflict Prediction Regression Model Comparative Analysis of Specific Incident Types

3.6.1 Field Validation Test 1: Merging and Diverging Location Ranking by Total Incidents

In this field validation test the ranking of merging and diverging locations from SSAM according to predicted total conflicts was compared to the same

locations using actual crash frequency. Three steps were performed in this test:

3.6.1.1 Conflict Ranking

In this step, SSAM was used to predict the expected total number of conflicts at each merging and diverging locations. Each location was simulated for five replications, each lasting 3600 simulation seconds (1 hour). Thus, the sum of all conflicts recorded over all five replications was divided by 5 to determine the average hourly conflict frequency in terms of conflicts per hour. The merging and diverging sections were then ranked based on their average hourly conflict frequency in descending order.

3.6.1.2 Crash Ranking

Crash ranking in this step was performed in such a way that the average yearly crash frequency for each merging and diverging locations was first determined by dividing the total number of crashes over the observation period by the number of years in the observation period. The 3 years observation period were used for all study locations. Merging and diverging locations were then ranked based on their average yearly crash frequency in descending order.

3.6.1.3 Ranking Comparison

The ranking derived from SSAM's conflict prediction (section 3.6.1.1) was compared to the rankings based on average yearly crash frequency (section 3.6.1.2). The Spearman rank correlation coefficient was used to determine the level of agreement between the two rankings. The Spearman rank correlation coefficient is often used as a nonparametric alternative to a traditional coefficient of correlation and can be applied under general conditions. The Spearman rank correlation coefficient (ρ_s) is calculated as shown in Equation 3.2. A score of 1.0 represents perfect correlation and a score of 0 indicates no correlation. An advantage of using (ρ_s) is that when testing for correlation between two sets of data, it is not necessary to make assumptions about the nature of the populations sampled.

$$\rho_s = 1 - \frac{6\sum {d_i}^2}{n(n^2-1)} \tag{3.2}$$

Where:

$d_i =$ the difference between two rankings for pair i.

$n =$ the number of paired ranked.

For hypothesis test, the Spearman rank correlation coefficient, ρ_s, was compared with the critical value, $\rho_{s\,(critical)}$.

For $n \leq 30$, $\rho_{s\,(critical)}$ can be read from the critical values table.

For $n > 30$, use:

$$\rho_{s\,(critical)} = \pm \frac{Z}{\sqrt{(n-1)}} \tag{3.3}$$

Where:

Z corresponds to the level of significance.

For example, if $\alpha = 0.05$, then $Z = 1.96$.If the absolute value of the test statistics ρ_s exceeds the positive critical value, then reject $H_O: \rho_s = 0$ and conclude that there is a correlation.

3.6.2 Field Validation Test 2: Merging and Diverging Location Ranking by Specific Incident Types

Comparative ranking procedures for Rear-end, crossing and lane-changing crash/conflict types were repeated in Field Validation Test 2 the same as Field Validation Test 1. These three conflict types were classified and counted by SSAM for each type. The average hourly conflict frequency for each conflict type was computed as in Field Validation Test 1, and these results were used to rank the merging and diverging sections for each conflict type. To provide type-specific crash frequencies, all crash reports from CDOT crash database were reviewed to determine whether it was a rear-end incident, crossing incident, or lane-changing incident. If the classification based on the crash type was not obvious, engineering judgment was applied to determine the most representative type. Average yearly crash frequencies was tabulated for each incident type, rank ordered, and compared using the

Spearman's rank correlation test, as in Field Validation Test 1. The results of this step demonstrated the capability of SSAM to accurately identify and rank merging and diverging sections .

3.6.3 Field Validation Test 3: Crash and Conflict Prediction Regression Model Paired Comparison.

In this field validation test, the correlation between conflicts obtained from SSAM and crashes were developed. Regression equations were established to estimate the average yearly crash frequencies at merging and diverging locations as a function of the average hourly conflict frequencies. The R^2 , Pearson chi-square and scaled deviance goodness-of-fit testing were used to determine the strength of the relationship between conflicts and crashes.

Regression equations to predict crashes based on volume were developed and compared with the conflict-based crash prediction model to study the relative capabilities of surrogate safety assessment. Generalized linear modeling GLM technique (Hauer, 1997; Sayed and Rodriguez, 1999) were used to calculate the expected crash frequency at each merging and diverging location, using the GENMOD procedure in the SAS® 9.3 statistical software package.

3.6.4 Field Validation Test 4: Crash and Conflict Prediction Regression Model Comparative Analysis of Total Incidents

This Field Validation Test consists of four steps and the details of the test are as follows:

Step A: Conflict prediction models for merging and diverging locations were developed using standard GLM procedures relating conflicts calculated by SSAM as a function of hourly traffic volume.

Step B: Crash prediction models for merging and diverging locations were developed using standard GLM procedures relating actual crash data obtained from CDOT accident database as a function of daily traffic volume.

Step C: The two prediction models were compared to determine whether or not the conflict prediction models can predict risk in a manner similar to the crash prediction model for merging and diverging locations with the same characteristics. The comparison consists of identification and ranking of crash/conflict prone locations. A crash/conflict prone location is defined as any location that exhibits a significantly higher number of crashes/conflicts as compared to a specific normal value. The normal value was provided by the volume-based crash/conflict prediction models. As stated previously, the Empirical Bayes (EB) technique improves the location-specific prediction and thus was used to identify hazardous locations. The EB refinement method identifies problem sites according to the following four-step process:

1. Estimate the predicted number of crashes/conflicts and its variance using the crash/conflict prediction model. This prediction can be

assumed to follow a gamma distribution (the prior distribution) with parameters α and β, where:

$$\beta = \frac{E(\Lambda)}{Var(\Lambda)} = \frac{\kappa}{E(\Lambda)} \; and \; \alpha = \beta . E(\Lambda) = \kappa \tag{3.4}$$

Where:

$Var(\Lambda) =$ the variance of the predicted crashes/conflicts.

$E(\Lambda) =$ predicted accident frequency

$\kappa =$ shape parameter

2. Determine the appropriate point of comparison based on the mean and variance values obtained in step 1. Usually the 50th percentile (P_{50}) or the mean is used as a point of comparison. P_{50} is calculated such that Equation 3.5 is satisfied.

$$\int_{0}^{P_{50}} \frac{\left(\frac{\kappa}{E(\Lambda)}\right)^{\kappa} . \; \lambda^{\kappa-1} . \; e^{-\left(\frac{\kappa}{E(\Lambda)}\right)\lambda}}{\Gamma(\kappa)} \, d\lambda = 0.5 \tag{3.5}$$

3. Calculate the EB safety estimate and the variance by rearranging Equations 2.23 and 2.24 respectively as shown in Equation 3.6 and Equation 3.7.

$$EB_{safety\ estimate} = \left(\frac{\kappa}{\kappa+E(\Lambda)}\right)E(\Lambda) + \left(\frac{E(\Lambda)}{\kappa+E(\Lambda)}\right)(count) \qquad (3.6)$$

where:

$count$ = observed accident frequency.

$$Var\left(EB_{safety\ estimate}\right) = \left(\frac{E(\Lambda)}{\kappa + E(\Lambda)}\right)^2 (\kappa) + \left(\frac{E(\Lambda)}{\kappa + E(\Lambda)}\right)^2 (count) \qquad (3.7)$$

This is also a gamma distribution (the posterior distribution) with parameters α_1 and β_1 defined as follows:

$$\beta_1 = \frac{EB}{Var(EB)} = \frac{\kappa}{E(\Lambda)} + 1\ and\ \alpha_1 = \beta_1.EB = \kappa + count \qquad (3.8)$$

Then, the probability density function of the posterior distribution is given by the following:

$$f_{EB}(\lambda) = \frac{\left(\frac{\kappa}{E(\Lambda)} + 1\right)^{(\kappa+count)} \lambda^{\kappa+count-1} e^{-\left(\frac{\kappa}{E(\Lambda)}+1\right)\lambda}}{\Gamma(\kappa + count)} \qquad (3.9)$$

4. Identify the location as crash/conflict-prone if there is significant probability that the location's safety estimate exceeds the P_{50} value (or the mean).

The location is prone if:

$$\left[1-\int_0^{P_{50}} \frac{\left(\frac{\kappa}{E(\Lambda)}+1\right)^{(\kappa+count)} \lambda^{\kappa+count-1} e^{-\left(\frac{\kappa}{E(\Lambda)}+1\right)\lambda}}{\Gamma(\kappa+count)}\, d\lambda\right] \geq \delta \tag{3.10}$$

Where:

δ is the desired confidence level (usually selected at 0.95).

The merging and diverging locations were then ranked in terms of priority for treatment once crash/conflict-prone sites were identified. Ranking problem sites enables the road authority to establish an effective road safety program, ensuring the efficient use of the limited funding available for road safety. Two techniques were suggested (Sayed and Rodriguez, 1999) that reflect different priority objectives for a road authority. The first ranking criterion is to calculate the ratio between the EB estimate and the predicted frequency as obtained from the GLM model (a risk-minimization objective). The ratio represents the level of deviation that the merge/diverge is away from a “normal” safety performance value, with the higher ratio representing a more hazardous location. The second criterion, the cost effectiveness objective, is a “potential for improvement” (PFI) criterion, which is calculated as the difference between the observed crash/conflict frequency and the volume-based estimate of “normal” crash/conflict frequency.

Step D: Two comparisons were undertaken. The first compared the locations identified as crash-prone to merging and diverging locations identified as conflict-prone. The second compared both the “risk ratio” and PFI merging

and diverging location rankings obtained using crash data to the corresponding rankings obtained using conflict data.

3.6.5 Field Validation Test 5: Crash and Conflict Prediction Regression Model Comparative Analysis of Specific Type Incidents

Field Validation Test 5 repeated the same comparative analysis as Field Validation Test 4 for the rear end, crossing and lane change crash/conflict types.

3.7 Goodness of Fit Measure

Three statistical measures were used to assess the goodness-of-fit of the regression models to the actual crash data to the merging and diverging locations.

The first measure was the Pearson chi-squared and computed by the following model:

$$\mathrm{P}earson\ \chi^2 = \sum_{i=1}^{n} \frac{[y_i - E(\Lambda_i)]^2}{Var(Y_i)} \tag{3.11}$$

Where:

$E(\Lambda_i)$ = the predicted crash frequency of merging or diverging location i

y_i = the actual crash frequency of merging or diverging location i

n = the number of merging or diverging location

The second statistical measure used was the scaled deviance. This is the likelihood ratio test statistic measuring twice the difference between the log-likelihood of the data under the developed model and its log-likelihood under the full or saturated model. The scaled deviance is computed by the following model:

$$SD = 2\sum_{i=1}^{n}\left[y_i \; ln\left(\frac{y_i}{E(\Lambda_i)}\right) - \; (y_i + \; \kappa_i) ln\left(\frac{y_i + \; \kappa_i}{E(\Lambda_i) + \; \kappa_i}\right)\right] \qquad (3.12)$$

There are several approaches to estimate the shape parameter κ of the negative binomial distribution with the method of maximum likelihood being the most widely used. The method of maximum likelihood will be used in this analysis.

The third goodness-of-fit measure is the R-squared which was defined by Miaou, 1996. It estimates the percentage of variation explained by a regression model. The model is based explicitly on the overdispersion parameter

The R-squared goodness-of-fit test was computed as:

$$R_\alpha^2 \; = 1 - \frac{\alpha}{\alpha_{max}} \qquad (3.13)$$

Where:

$\alpha =$ the overdispersion parameter estimated in the model

$\alpha_{max} =$ the overdispersion parameter estimated in the negative binomial model, the model with only a constant term and an overdispersion parameter.

4. Test Results and Discussion

This section presents the results of the field validation testing effort. The experimental procedure, prior to statistical testing, is summarized as follows. A set of twenty-one interchanges, selected from field sites in Colorado, North America, and were modeled in VISSIM. Each merge/diverge model was simulated for five replications for 1 hour of simulated time. The corresponding five output files (i.e., TRJ files) from VISSIM were then imported into SSAM for identification of conflicts and computation of the surrogate measures of safety for each conflict event. SSAM was configured to use conflict identification threshold values. The maximum time-to-collision (TTC) and maximum post-encroachment time (PET) values used were 1.5 seconds and 5.0 seconds, respectively. The results of the SSAM analysis consists of the number of total conflicts and the number of conflicts of each type of vehicle-vehicle interaction: crossing, rear end, and lane changing. Before any statistical inferences were applied, the outliers were identified and removed from the dataset.

Figure 4.1 shows five files added to the case files section. These files were obtained from a model simulated for five replications. Note that the files selected have a .trj extension. The default maximum TTC and maximum PET values were not changed. Also the threshold angles (30 ° and 85 °) which were determined by experimentation were not changed.

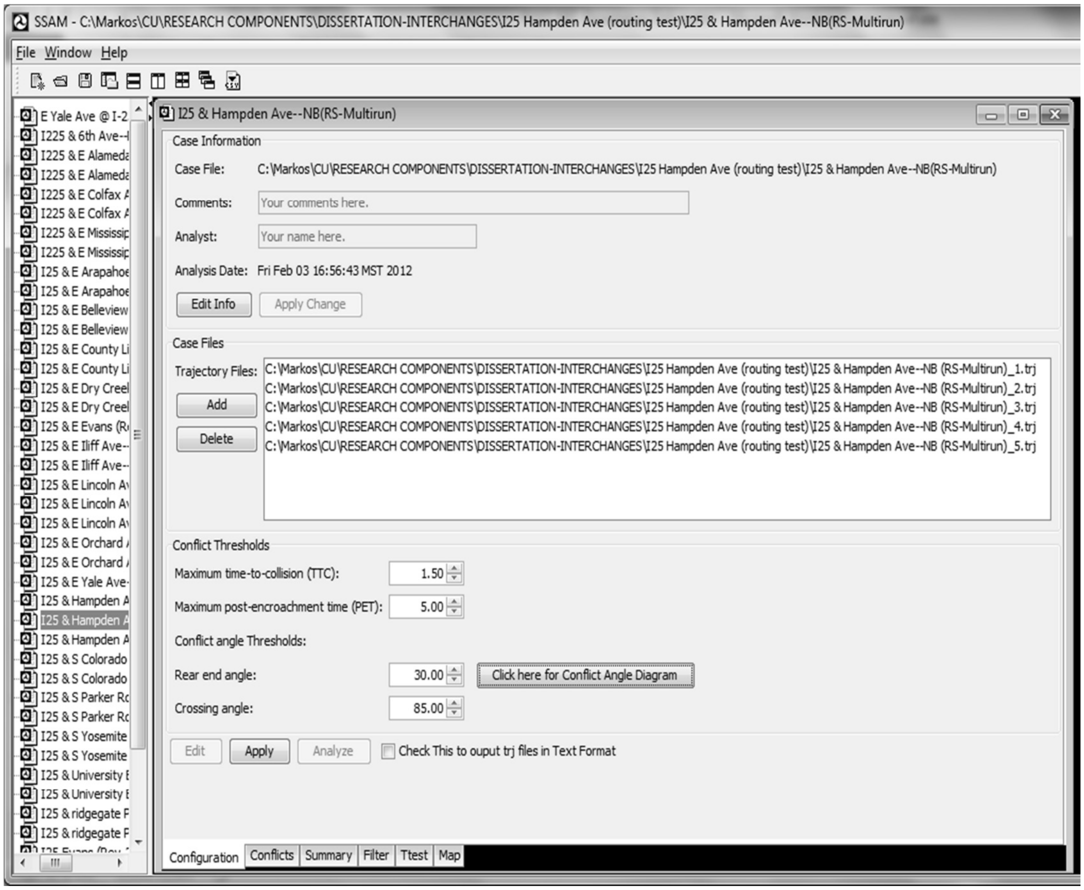

FIGURE 4.1. SCREEN CAPTURE. SSAM SCREEN—CONFIGURATION TAB

SSAM contains a built-in feature to visualize conflicts. The conflicts can be visualized within a Map tab or imported to SSAM as VISSIM .inp file. Typically, the Map file is the graphic file of the simulated network for the case document. The VISSIM .inp file is the VISSIM network file that has been simulated and has generated the vehicle trajectory file that was used for

SSAM analysis. Figure 4.2 shows the display of conflicts in the Map view section. The average hourly conflict counts for each merge/diverge locations is provided in Appendix E.

FIGURE 4.2 SCREEN CAPTURE. SSAM SCREEN – MAP TAB VIEW AT I-25 & E HAMPDEN AVE

4.1 Field Validation Test 1: Merging and Diverging Location Ranking by Total Incidents

Validation Test 1 is a comparison of the ranking of merge/diverge locations based on average hourly total conflict frequency versus the ranking of merge/diverge locations based on average yearly total crash frequency. The Spearman rank correlation coefficient (ρ_s) values of ranking based on total conflict comparison were 0.486 and 0.551 for merging and diverging movements respectively, these values are significant at 95 percent level of confidence.

As a basis of comparison, the merge/diverge locations were also ranked in terms of total ADT values, and these were also compared with the ranking based on average yearly total crash frequency. The Spearman rank correlation coefficient (ρ_s) values of this ranking comparison were 0.419 (significant at a 95 percent level of confidence) and 0.309 (not significant at a 95 percent level of confidence) for merging and diverging movements respectively, these values are shown in Table 4.2.

In general, the Spearman rank correlation tests showed that a higher correlation was found for both merge and diverge movements with merge/diverge locations rankings based on conflicts than ADT.

4.2 Field Validation Test 2: Merging and Diverging Location Ranking by Specific Incident Types

Validation Test 2 repeats the same comparative ranking procedures as for validation test 1 for the subsets of crash/conflict types: rear end and lane changing. There were no crossing conflicts recorded to perform the ranking comparison for crossing type incidents. Table 4.1 displays the distribution of conflicts and crashes by incident type. There were 1 percent merging and 4 percent diverging lane changing conflicts were recorded, while the remaining portion were rear end conflicts. However the proportion of crashes of the lane changing and rear end maneuvers at merge and diverge, was 26 percent and 23 percent respectively.

There were significant differences between conflict distributions by type and actual crash distributions by type. The ratios of conflicts-per-hour to crashes-per-year for total incidents at merge and diverge were 117 and 137 respectively. The ratios of conflicts-per-hour to crashes-per-year for rear-end and lane-change incidents at merge were 156 and 5 respectively. However the ratios of conflicts-per-hour to crashes-per-year for rear-end and lane-change incidents at diverge are 169 and 26 respectively. It seems plausible that conflicts-to-crashes ratios are higher for less dangerous incidents. That is, accepting that rear-ends are generally less severe than lane-change, there is an abundance of these “lower risk” conflicts. In all the simulation scenarios, rear-end conflict events made up the bulk of the total conflicts.

It was also observed that the total number of diverging conflicts were 42% higher than that of the merging conflicts. Similarly, the total number of diverging crashes are 22% higher than that of merging crashes . This was

consistent with the study by Cillo (1967) and Lundy (1966) which showed that the accident rates of off-ramps are higher than the accident rates of on-ramps.

Figure 4.3 illustrates an example of a conflict, where some vehicles are angling across lanes and have abruptly cut in front of other vehicles that must decelerate to avoid collision.

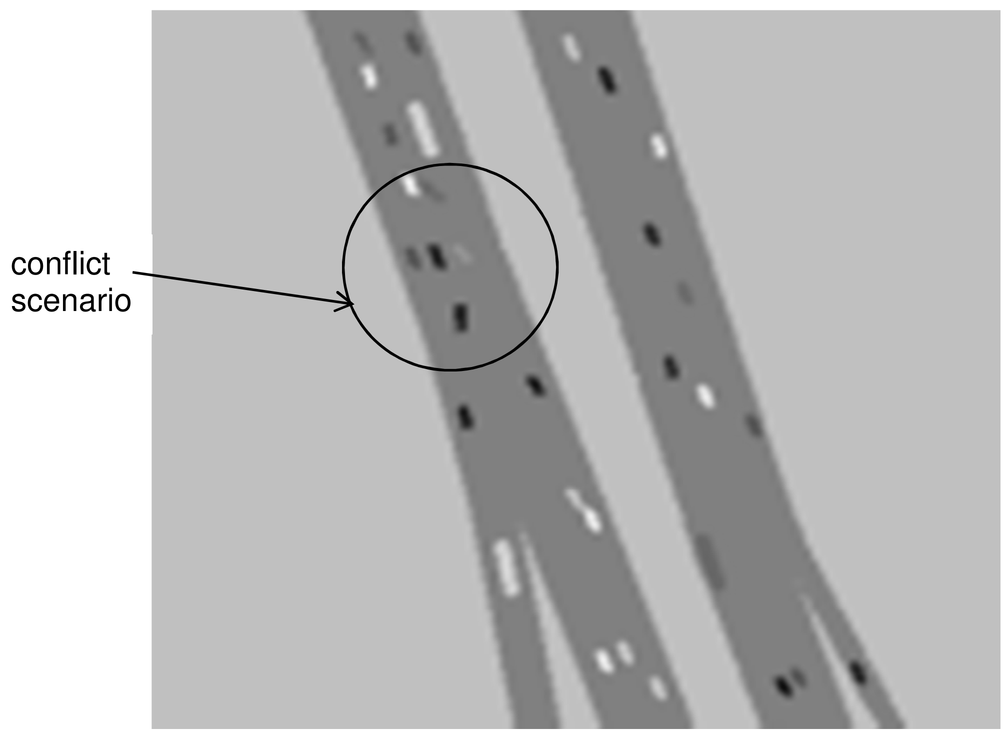

FIGURE 4.3 SCREEN CAPTURE. VISSIM CONFLICT SCENARIO RESULTING FROM LANE CHANGE MANEUVER

A higher proportion of rear-end conflict obtained from SSAM was consistent with the study reported on crash prediction models on urban signalized intersections. Guttman, Pu, Sayed, and Shelby (2008) modeled signalized intersections in VISSIM and simulated under AM peak hour traffic conditions. The conflict analysis was done using SSAM and found that the proportion of crossing, rear-end, and lane-change conflicts were 1.7 percent, 91.0 percent, and 7.3 percent respectively.

Moving on to the results of the ranking tests and looking into Table 4.2, there is a significant correlation between conflicts and crashes when considered by conflict type. The Spearman rank correlation coefficient (ρ_s) value at merge for rear end incident ranking comparison was 0.403, which is significant at a 95 percent level of confidence. Whereas, the Spearman rank correlation coefficient (ρ_s) value at diverge for rear end incident ranking comparison was 0.456, which is also significant at a 95 percent level of confidence. Moreover, the Spearman rank correlation coefficient (ρ_s) value at merge and diverge for the lane changing incident ranking comparison were 0.540 (significant at a 95 percent level of confidence) and 0.550 (significant at a 95 percent level of confidence) respectively.

For comparison, the merge/diverge locations were ranked on the basis of total ADT values, and this was also compared with the rankings based on rear-end and lane-change crashes. Rear-end ranking comparisons at merge was not significant at 95 percent level of confidence. Moreover, the Spearman rank correlation coefficient (ρ_s) at diverge for rear-end incident ranking comparison was not significant at a 95 percent level of confidence. However, the Spearman rank correlation coefficient (ρ_s) at both merge and diverge for

lane-changing ranking comparison were significant at a 95 percent level of confidence.

In general, rank correlation testing showed a significant correlation between rear-end conflicts and rear-end crashes and between lane-change conflicts and lane-change crashes. Also, the rank correlation tests have shown that stronger correlation was observed based on conflict than ADT.

Table 4.1 Distribution of crashes and conflicts by incident type

	Incident Type					
	Merge			**Diverge**		
	Rear End	Lane Change	All Type	Rear End	Lane Change	All Type
Average Hourly Conflicts	36,572	370	36,942	50,358	2,219	52,577
Percentage of Conflicts by Type	99%	1%	100%	96%	4%	100%
Average Yearly Crashes by Type	234	82	315	298	87	385
Percentage of Crashes by Type	74%	26%	100%	77%	23%	100%
Conflict-to-crash ratio	156	5	117	169	26	137

Table 4.2 Correlation coefficients by incident type

Ranking based on	Incident Type					
	Merge			Diverge		
	Rear End	Lane Change	All Type	Rear End	Lane Change	All Type
Crashes and Conflicts	0.403	0.540	0.486	0.456	0.550	0.551
Crashes and ADT	0.318	0.533	0.419	0.217	0.551	0.309

4.3 Field Validation Test 3: Crash and Conflict Prediction Regression Model Paired Comparison

Validation Test 3 assessed the correlation between conflicts and crashes by using regression to construct a conflicts-based model to predict crash frequencies at merging and diverging locations. Additionally, the capabilities of conflict-based crash-prediction were compared to a traditional volume-based crash-prediction model.

A standard generalized linear modeling (GLM) approach was used to establish a model of the expected crashes as a function of mainline, merging, and diverging ADT. Crashes in these models are expressed in terms of average yearly crash frequency, as a function of the model variables which are the ADT volumes of the mainline, merging, and diverging (in vehicles per

day) or $ADT_{mainline}$, ADT_{merge}, and $ADT_{diverge}$, respectively. The estimates of parameters for these models are shown in Table 4.3 and Table 4.4. However, conflicts are expressed in terms of average hourly conflicts (conflicts per hour).

Table 4.3 and Table 4.4 show the estimates of the parameters of the total crash model at merging and diverging locations respectively. Furthermore, the table shows that both the Pearson chi-squared and the scaled deviance values were not significant at the 90- percent confidence level, indicating a good fit. Moreover, these models were compared using the R-squared goodness-of-fit test (Miao, 1996), and the results conform to those of the Pearson chi-squared and the scaled deviance. Moreover, graphs corresponding to Model (1) and Model (2) were provided in Figure 4.4 and Figure 4.5 respectively.

Table 4.3 Prediction model of total crashes as a function of mainline ADT and merging ADT

Model (1) $\text{Total Crash/yr}_{merge} = 2.12E\text{-}04 \times ADT_{mainline}^{0.773} \times ADT_{merge}^{0.209}$					
Degree of Freedom	**R-Squared R^2**	**Scaled Deviance**	**Pearson χ^2**	$\chi^2_{0.1,30}$	**Shape Parameter**
30	0.54	32.24	33.61	40.26	5.08
	Variable			**Coefficient**	
	Constant			2.12E-04	
	$ADT_{mainline}$			0.773	
	ADT_{merge}			0.209	

Table 4.4 Prediction model of total crashes as a function of mainline ADT and diverging ADT

Model (2) $\text{Total Crash/yr}_{diverge} = 0.061 \times ADT_{mainline}^{0.058} \times ADT_{diverge}^{0.478}$					
Degrees of Freedom	**R-Squared R^2**	**Scaled Deviance**	**Pearson χ^2**	$\chi^2_{0.1,31}$	**Shape Parameter**
31	0.82	34.72	34.39	41.42	30.21
	Variable			**Coefficient**	
	Constant			0.061	
	$ADT_{mainline}$			0.058	
	$ADT_{diverge}$			0.478	

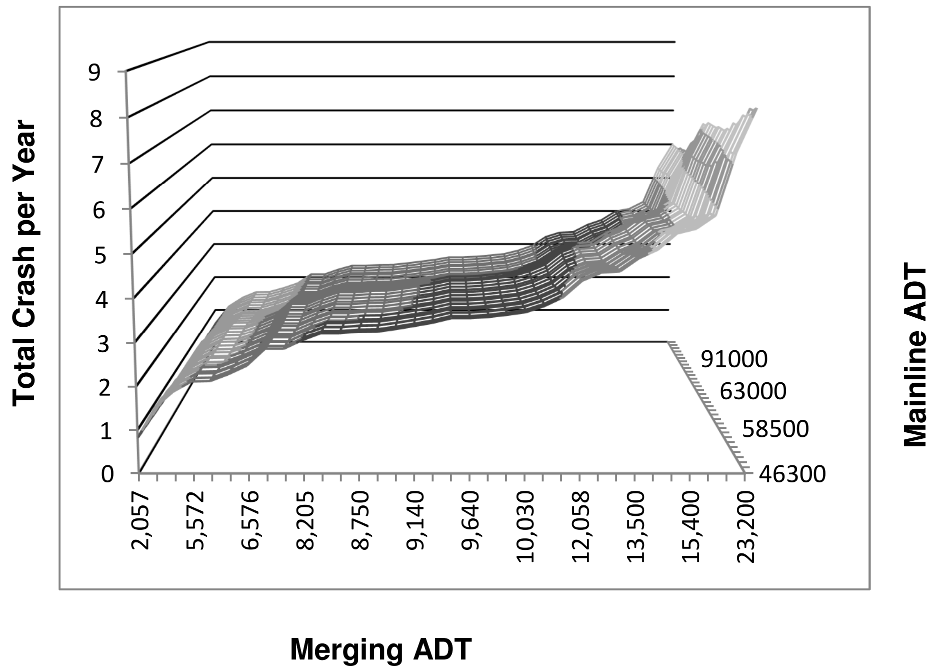

FIGURE 4.4 TOTAL CRASH AS A FUNCTION OF MAINLINE ADT AND MERGING ADT

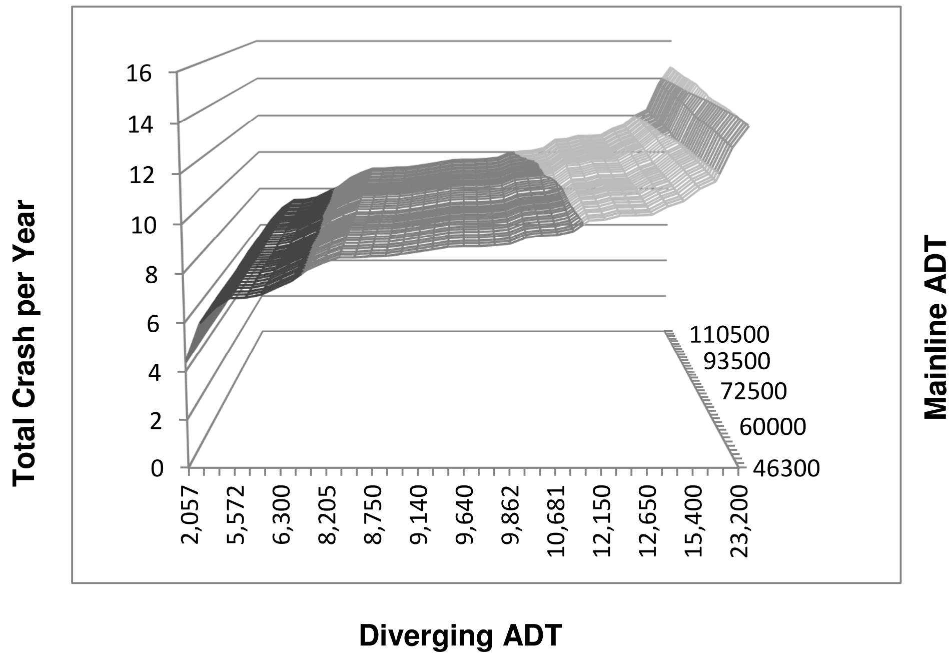

FIGURE 4.5 TOTAL CRASH AS A FUNCTION OF MAINLINE ADT AND DIVERGING ADT

However, another regression technique was then employed to relate the actual crashes frequency to the conflict frequency predicted by SSAM. It was assumed that both real life crashes and real-life conflicts were discrete random events. Therefore, the validation test technique assumed that both crashes and simulated conflicts follow a negative binomial distribution. Table 4.5 and Table 4.6 show the estimate of the parameters of these regression equations. These parameter estimates were obtained using a SAS GENMOD statistical tool that was developed to iteratively update the likelihood equations. Also, graphs corresponding to Model (3) and Model (4) were provided in Figure 4.6 and Figure 4.7 respectively.

The scaled deviance and the Pearson chi-squared values for both models were not significant at the 90-percent confidence level, indicating good fit of the regression equation. Moreover, the result of the R-squared goodness-of-fit test conforms to those of the Pearson chi-squared and the scaled deviance and found to have values of 0.57 and 0.90 for merging and diverging maneuvers respectively.

Table 4.5 Prediction model of total crashes as a function of conflicts at merge

Model (3)	$\text{Total Crash/yr}_{merge} = 1.072 \times \text{Total Conflicts}_{merge}^{0.373}$				
Degree of Freedom	**R-Squared R^2**	**Scaled Deviance**	**Pearson χ^2**	$\chi^2_{0.1,31}$	**Shape Parameter**
31	0.57	31.91	31.00	41.42	5.40
	Variable			**Coefficient**	
	Constant			1.072	
	Conflicts_{merge}			0.373	

Table 4.6 Prediction model of total crashes as a function of conflicts at diverge

Model (4)	$\text{Total Crash/yr}_{diverge} = 2.617 \times \text{Total Conflicts}_{diverge}^{0.204}$				
Degree of Freedom	**R-Squared R^2**	**Scaled Deviance**	**Pearson χ^2**	$\chi^2_{0.1,32}$	**Shape Parameter**
32	0.90	35.33	36.19	42.58	52.36
	Variable			**Coefficient**	
	Constant			2.617	
	$\text{Conflicts}_{diverge}$			0.204	

In the previous studies with similar traffic facilities, traditional multiple regression models based on the negative binomial distribution were performed to determine the relationships between accidents and the geometric design and traffic volume characteristics of interchanges. These models explained between 10 percent and 42 percent of the variability in the accident data. For example, in FHWA-RD-97-106, Statistical Models of Accidents on Interchange Ramps and Speed Change Lanes—*Report*, linear regression models were applied to fit 3 years of crash data for a set of the 551 ramps, 276 deceleration lanes, and 192 acceleration lanes, yielding an R-squared value of 0.38 for the total crash frequency

The conflicts-based model and volume-based model were compared using the R-squared goodness-of-fit test. For crash prediction model based on volumes, the *R*-squared values were recorded to be 0.54 and 0.82 for merge and diverge approach respectively. Similarly, for crash prediction model based on simulated conflict, the *R*-squared values were recorded to be 0.57 and 0.90 for merge and diverge approach respectively. Thus, the conflict based model exhibited a better correlation than the volume-based model. However, both the volume-based model and the conflict based model had a better correlation than the traditional multiple regression model.

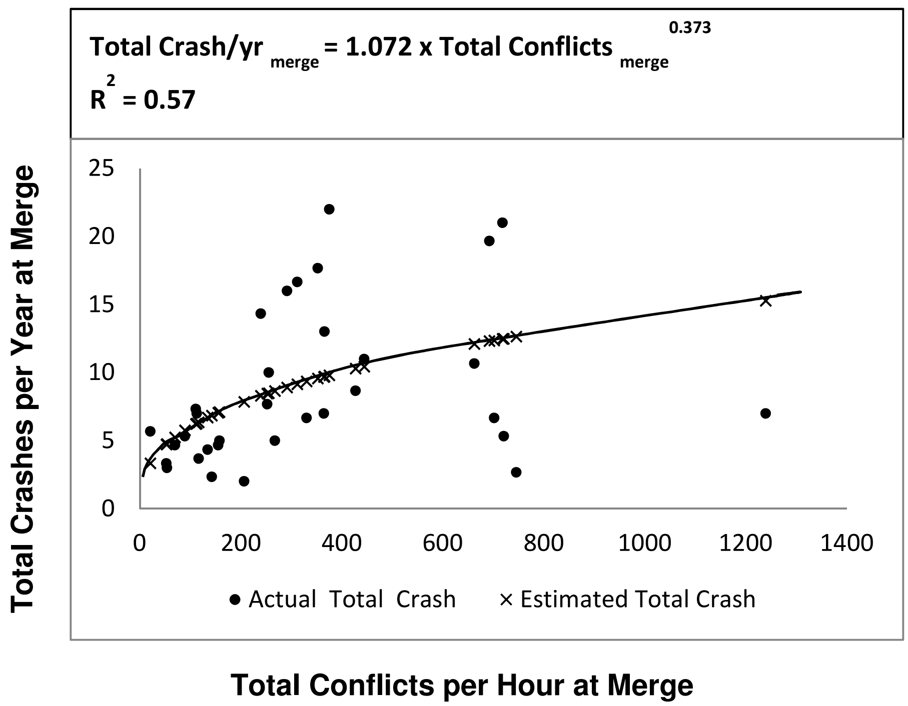

FIGURE 4.6 TOTAL CRASH AS A FUNCTION OF TOTAL CONFLICT AT MERGE

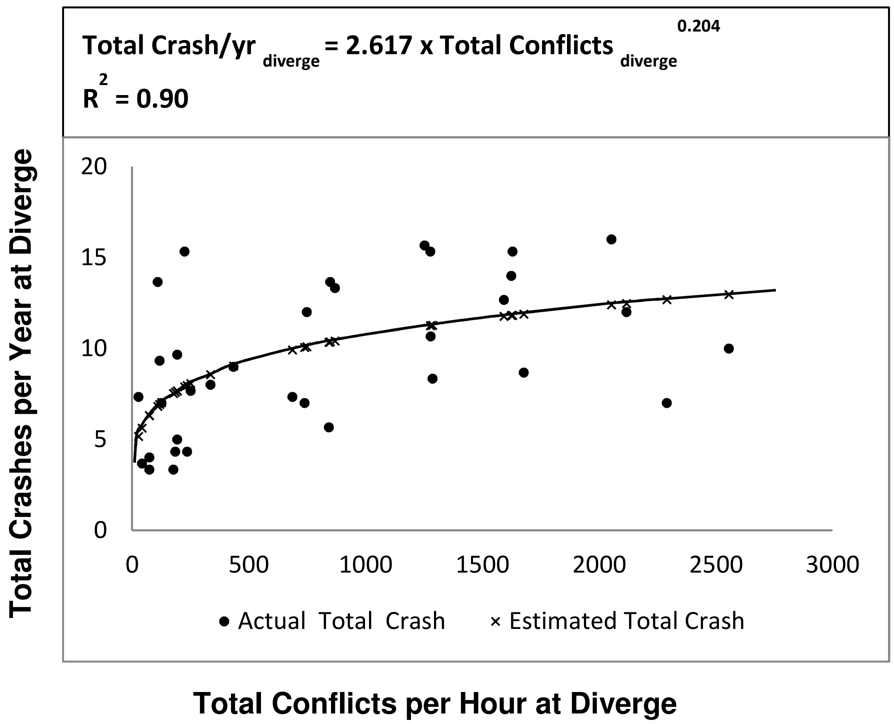

FIGURE 4.7 TOTAL CRASH AS A FUNCTION OF TOTAL CONFLICT AT DIVERGE

Figures 4.4 through Figure 4.7 helped estimate crashes as a function of ADT and conflict frequency at both merge and diverge section of freeways.

In the ADT approach (Model 1 and Model 2), merge and diverge locations that have the same ADT would have the same crash frequencies, which is not always true. On the contrary, looking at crash as a function of conflict (Model 3 and Model 4), it explained the operational differences and vehicle dynamics of locations. The conflict analysis considered the dynamics of simulate traffic systems on a vehicle-by-vehicle basis by updating position, speed, acceleration, lane position, and other variables on time steps, such as on a seconds basis, as the vehicles interact with other vehicles and roadway geometrics. In the evaluation of surrogate safety measures, microscopic simulations model the key driver behaviors (car following, gap acceptance, lane changing) that affect the occurrence of traffic crashes. At merging locations simulation models allow vehicles to merge safely by accelerating in the adjacent lane, which occurs in the real world. At diverging location simulation models allow vehicles to diverge safely by deceleration in the adjacent lane, which occurs in the real world as well.

In general, conflict models (SSAM) can be used to assess the relative safety of a pairs of merge/diverge design alternatives. Under equivalent traffic conditions (e.g., traffic volumes and truck percentage), for both merge/diverge design alternatives, SSAM could exhibit statistically significant differences in the total number of conflicts, the number of conflicts by type (lane-change, or rear-end incidents). This helps to conclude that one design exhibited a higher frequency of conflicts, than the alternative design. This type of assessment helps the decision-making process about which design is the safer of the two.

Therefore, models that relate total crash and total conflict (Model 3 and Model 4) provided a more realistic output to represent the real world crash frequencies.

4.3.1 Illustration

After identifying the locations that exhibited abnormal crash/conflict frequencies, they were examined for a possible explanation as to why that happened.

To illustrate, a corridor on I-25 from E. Dry Creek Rd to E. Hampden Ave was taken. After recording crash frequencies at the selected data points, high number of merging and diverging crashes were observed both in the north and south bound directions, see Appendix D. Looking at each crash, congestion builds throughout the rush hour even though the volumes are not that much different. As congestion builds so does the chance for something to go wrong which in this case could be the crash counts. Entering and exiting volumes, especially with I-225 (a high volume interstate freeway) located at the north end can have an effect as large volume introduced from/to I-225.

Looking at the same corridor, the number of conflicts recorded by SSAM at merge both at E. Dry Creek Rd and E. Belleview Ave were high. This happened because the acceleration lengths at these locations were very short to allow traffic to change lane and merge with the through traffic. According to AASHTO (2004), acceleration lane should have sufficient length to permit adjustments in speeds of both through and entering vehicles so that

the driver of the entering vehicle can position himself in a safe and comfortable manner in a through traffic stream and maneuver into it before reaching the end of the acceleration lane.

In driving north the same corridor, but studying the recorded conflict at diverging locations, E. Dry Creek Rd exhibited the highest number of conflict whereas Belleview exhibited the lowest number of conflicts. The main reason for this was the discrepancy of the composition of traffic at these locations. The percentage of trucks at E. Dry Creek Rd and E. Belleview Ave were 6.6% and 5.1% respectively, while geometric and other traffic data remain the same. Therefore, the high proportion of truck contributed to the increased number of conflicts.

Moreover, there was evidence to suggest that the occurrence of conflicts and crashes may be somewhat distinct while still significantly related. For example, for the same corridor defined above, at E. Dry Creek Rd in the north bound direction the number of recorded crashes were the lowest while the corresponding number of conflicts recorded by SSAM were the highest. This is true both at the merge and diverge locations.

4.4 Field Validation Test 4: Crash and Conflict Prediction Regression Model Comparative Analysis for Total Incidents.

4.4.1 Development of Conflict Prediction Regression Models for Total Incident

The first step of this validation test included developing a volume-based conflict prediction model and a volume-based crash-prediction model. The volume-based crash prediction model was previously developed in Validation Test 3, Model (1) and Model (2). The parameters of those models are shown in Table 4.3 and Table 4.4 respectively.

A volume-based conflict-prediction model was developed using the same procedure but relating conflicts to traffic volumes on the mainline, merge and diverge areas. Note that the conflicts identified by SSAM were based on the peak-hour volumes used for simulation. The variables used in the conflict-prediction model were: $PHV_{mainline}$, vehicle per hour (VPH) on the mainline approach, PHV_{merge}, vehicle per hour (VPH) on the merge location, and $PHV_{diverge}$, vehicle per hour (VPH) on the diverge location. Table 4.7 (Model 5) and Table 4.8 (Model 6) shows the estimates of the parameters for total conflict prediction model at merge and diverge location respectively. The *R*-squared values were assessed and recorded to be 0.22 and 0.29 for merging and diverging locations respectively.

Table 4.7 Prediction model of conflicts as a function of mainline PHV and merging PHV

Model (5)

$$\text{Total Conflict/hr}_{\text{merge}} = 0.071 \times \text{PHV}_{\text{mainline}}^{0.659} \times \text{PHV}_{\text{merge}}^{0.394}$$

Degrees of Freedom	R-Squared R^2	Scaled Deviance	Pearson x^2	$x^2_{0.1,30}$	Shape Parameter
30	0.22	35.71	46.90	40.26	1.97

Variable	Coefficient
Constant	0.071
$\text{PHV}_{\text{mainline}}$	0.659
$\text{PHV}_{\text{merge}}$	0.394

Table 4.8 Prediction model of conflicts as a function of mainline PHV and diverging PHV

Model (6)

$$\text{Total Conflict/hr}_{\text{diverge}} = 1.51\text{E-05} \times \text{PHV}_{\text{mainline}}^{1.264} \times \text{PHV}_{\text{merge}}^{0.965}$$

Degrees of Freedom	R-Squared R^2	Scaled Deviance	Pearson x^2	$x^2_{0.1,29}$	Shape Parameter
29	0.29	34.99	53.51	39.09	1.70

Variable	Coefficient
Constant	1.51E-05
$\text{VPH}_{\text{mainline}}$	1.264
$\text{VPH}_{\text{merge}}$	0.965

4.4.2 Identification of Accident Prone Locations (APL)

The second step of this validation test was the identification of crash-prone locations and conflict-prone locations. This test determined whether the conflict prediction equation can predict risk in a manner similar to the crash prediction equation for interchanges with the same characteristics, by identifying accident prone locations (APL). A crash/conflict prone location is defined as any location that exhibits a significantly higher number of crashes/conflicts as compared to a specific normal value, which in this test is provided by the volume-based crash/conflict prediction models (Sayed and Rodriguez, 1999)

Empirical Bayes (EB) method combines the information contained in crash counts of a specific highway segment with an estimate of its safety performance derived from safety performance function obtained from GLM models to increase the precision of estimation. Also, the EB method corrects for the regression-to-mean bias.

Comparison between crash and conflict prone locations at merge and diverge locations are shown in Tables 4.9 and 4.10 respectively and a summary was displayed in Table 4.11. Accordingly fewer locations were identified as accident prone by regression Models (1) and (2) based on actual crash than those identified by the regression Model (5) and (6) based on simulated conflicts records.

Table 4.11 also showed that 5 APL and 2 APLs were common between the total crash/conflict models at merging and diverging location respectively. This indicates a poor agreement between the total crash and total conflict

models in identifying incident prone locations at both merging and diverging location. These 5APL merging locations can thus be considered by decision-makers or safety analysts as candidate for remedial treatments before crashes occur. Table 4.12 shows the average total crashes and total conflicts based on incident proneness of locations.

4.4.3 Illustration

Consider a location where traffic merging from E. Hampden Ave onto I-25 in the NB direction. This location has an observed total crash rate of 13.0 crashes/ year, applying the model of the safety performance function developed from GLM, the expected crash value is 12.4 crashes/year with a variance of 15.0 (crashes/year)^2. The P_{50} value for the Gamma Distribution was calculated as 8.2 crashes/year. The EB safety and its variance are 12.8 crashes/year and 6.5 (crashes/year)^2 respectively. It was determined that the probability of having crashes less than P_{50} is 2.39%. This means that there is a significant probability (97.61%) of exceeding the P_{50} value and this location can be considered as accident-prone.

Also consider a location where traffic diverging from I-25 on the SB direction to S. University Blvd. This location has a simulated total conflict rate of 687 conflicts/hour, applying the model of the safety performance function developed from GLM, the expected conflict value was 493 conflicts/hour with a variance of 404,040 (conflicts/hour)^2. The P_{50} value for the Gamma Distribution was calculated as 673 conflicts/hour. The EB safety and its variance were 686 conflicts/hour and 684 (conflicts/hour)^2 respectively. It was determined that the probability of having crashes less than P_{50} is 31.3%. This means that this location will not be considered as accident-prone, so the

engineering improvements may not be cost effective to reduce the number of accidents related to diverging maneuvers.

4.4.4 Ranking Locations

Once crash/conflict-prone sites were identified, the next step of this test was to rank the locations in terms of priority for treatment. Two techniques were used: (1) the ratio between the EB estimate and the predicted frequency obtained from the GLM regression equations (a risk-minimization objective) and, (2) the PFI (a cost-effectiveness objective). Table 4.9 and Table 4.10 showed the Spearman rank-correlations for both the Ratio and PFI rankings. At merge, the Spearman rank correlation coefficient (ρ_s) values of the Ratio and PFI ranking comparisons were 0.118 and 0.045, respectively, indicating an insignificant correlation between locations with "excessive crashes" and locations with "excessive conflicts," relative to values estimated by volume-based crash- and conflict-prediction models respectively.

At diverge, the Spearman rank correlation coefficient (ρ_s) values of the Ratio and PFI ranking comparisons were -0.196 and -0.110, respectively, indicating an insignificant correlation between locations with "excessive crashes" and locations with "excessive conflicts," relative to values estimated by volume-based crash- and conflict-prediction models respectively.

Table 4.9 Comparison between total crash and total conflict prone locations at merge.

ID	Actual Total Crash	Simulated Total Conflict	Model Estimate (E(X))		EB Estimate		Crash Prone Location	Conflict Prone Location
			Crash	Conflict	Crash	Conflict		
1	4.7	70	5.7	206	5.1	71	no	no
1a	3.7	117	5.3	182	4.5	118	no	no
2	7.3	111	6.7	271	7.0	112	no	no
2a	5.0	158	6.5	266	5.7	159	no	no
3	3.3	53	10.4	416	5.6	55	no	no
4	5.3	721	11.6	534	7.2	720	no	**yes**
4a	10.7	663	11.4	517	10.9	662	no	**yes**
5	19.7	693	11.7	512	17.3	692	**yes**	**yes**
5a	7.0	365	11.4	456	8.4	365	no	**yes**
6	17.7	353	11.9	546	15.9	354	**yes**	**yes**
6a	5.0	268	10.6	441	6.8	269	no	no
7	21.0	719	12.1	456	18.4	718	**yes**	**yes**
7a	6.7	702	12.0	471	8.2	701	no	**yes**
8	13.0	366	12.4	544	12.8	367	**yes**	**yes**
8a	6.7	331	12.0	530	8.3	332	no	**yes**
9	7.0	113	8.7	316	7.6	114	no	no
9a	2.0	207	9.9	368	4.7	208	no	no
10a	7.7	253	10.0	367	8.5	254	no	no
11	11.0	445	10.4	387	10.8	445	no	**yes**
12	16.0	292	9.8	349	13.9	292	**yes**	no
12a	22.0	376	9.1	302	17.4	376	**yes**	**yes**
13	5.7	21	5.9	205	5.8	23	no	no
14a	4.7	156	7.1	260	5.7	157	no	no
15	10.0	256	5.6	190	7.9	255	no	no
15a	2.3	143	4.5	128	3.5	143	no	no
16a	7.0	1240	7.0	259	7.0	1233	no	**yes**
18	2.7	746	7.3	266	4.6	742	no	**yes**
18a	16.7	312	7.2	262	12.8	312	no	no
19	3.0	54	7.1	255	4.7	56	no	no
19a	14.3	240	7.2	269	11.4	240	no	no
20	8.7	428	8.0	327	8.4	427	no	**yes**
20a	5.3	90	6.7	227	5.9	91	no	no
21	4.3	135	4.8	157	4.6	135	no	no

Spearman rank correlation based on Ratio ranking method = 0.118

Spearman rank correlation based on PFI ranking method = 0.045

Table 4.10 Comparison between total crash and total conflict prone locations at diverge

ID	Actual Total Crash	Simulated Total Conflict	Model Estimate (E(X))		EB Estimate		Crash Prone Location	Conflict Prone Location
			Crash	Conflict	Crash	Conflict		
1	7.0	127	8.2	245	7.9	128	no	no
1a	4.0	75	7.1	181	6.5	76	no	no
2	5.0	194	9.3	455	8.3	195	no	no
2a	7.7	251	8.8	433	8.5	252	no	no
3a	7.3	28	10.7	929	9.8	30	no	no
4	7.0	2291	10.0	1799	9.2	2291	no	**yes**
4a	10.0	2557	9.6	1659	9.7	2556	no	**yes**
5	10.7	1279	11.9	1751	11.6	1279	no	**yes**
5a	13.3	870	11.2	1317	11.8	871	no	**yes**
6	12.7	1593	11.5	2012	11.8	1593	no	**yes**
6a	7.0	739	8.9	1197	8.4	740	non	**yes**
7	15.7	1253	10.9	1276	12.2	1253	**yes**	**yes**
7a	8.7	1678	10.7	1375	10.2	1678	no	**yes**
8	14.0	1624	14.5	2054	14.3	1624	**yes**	**yes**
8a	8.3	1287	13.6	1927	12.0	1288	no	**yes**
9	8.0	336	6.9	548	7.1	337	no	no
9a	9.0	435	9.2	801	9.1	436	no	no
10	15.3	1278	10.6	934	11.8	1277	no	**yes**
10a	5.7	844	10.1	806	9.0	844	no	**yes**
11	12.0	2118	10.8	912	11.1	2116	no	**yes**
11a	13.7	849	9.9	476	10.9	848	no	**yes**
12a	7.3	687	7.7	493	7.6	686	no	no
13a	13.7	110	7.1	223	8.4	111	no	no
14b	3.3	177	9.1	400	7.8	178	no	no
15	9.3	119	7.1	195	7.5	120	no	no
15a	3.3	75	4.4	75	4.3	75	no	no
16a	16.0	2054	9.3	399	10.8	2047	no	**yes**
18	4.3	186	9.1	416	8.0	187	no	no
18a	12.0	749	8.9	399	9.6	748	no	**yes**
19	4.3	236	8.8	379	7.8	237	no	no
19a	15.3	1630	9.4	430	10.8	1625	no	**yes**
20	15.3	225	11.9	695	12.9	226	**yes**	no
20a	9.7	194	7.7	285	8.1	195	no	no
21a	3.7	43	6.0	127	5.6	44	no	no

Spearman rank correlation based on Ratio ranking method = -0.196

Spearman rank correlation based on PFI ranking method = -0.110

Table 4.11 Summary of APLs of total incidents

Incident location	**merging**	**diverging**
Number of APLs identified based on total crash	6	3
Number of APLs identified based on total conflict	14	17
Common number of APLs identified based on both total crash and total conflict	5	2

Table 4.12 Average total crashes and total conflicts based on incident proneness of locations

Location	**Crash Prone**		**Conflict Prone**	
	Yes	**No**	**Yes**	**No**
Merge	18.2	6.6	582	160
Diverge	15.0	8.9	1453	206

4.5 Validation Test 5: Crash and Conflict Prediction Regression Model Comparative Analysis for Specific Type of Incidents.

4.5.1 Development of Conflict Prediction Models for Specific Incident Types

Validation test 5 repeats the same process for validation Test 4 but for each incident type (rear-end, lane-changing, and crossing). Due to zero number of observed crossing incidents, crossing-type incidents were excluded from this analysis.

In addition, lane change type incidents were also excluded from the analysis because the models didn't converge to a finite value. This phenomenon is due to the condition that the relative Hessian convergence criterion has been exceeded. This criterion detects the occasional case where the change in parameter convergence is satisfied in the GENMOD procedure by the SAS statistical software package. This is perhaps due to the relatively low number of lane-changing incidents (both crashes and conflicts).

Table 4.13 through 4.16 show the estimates of the parameters for the rear-end incidents, Model (7) through (10) respectively, based on ADT and PHV values. The model parameters were assessed and recorded.

Table 4.13 Prediction model of rear-end crashes as a function of mainline ADT and merging ADT

Model (7)

$$\text{Rear-End Crashes/yr}_{\text{merge}} = 9.64\text{E-05} \times \text{ADT}_{\text{mainline}}^{0.827} \times \text{ADT}_{\text{merge}}^{0.195}$$

Degree of Freedom	R-Squared R^2	Scaled Deviance	Pearson x^2	$x^2_{0.1,30}$	Shape Parameter
30	0.43	33.33	33.03	40.26	2.61

Variable	Coefficient
Constant	9.64E-05
ADT $_{mainline}$	0.827
ADT $_{merge}$	0.195

Table 4.14 Prediction model of rear-end conflicts as a function of mainline PHV and merging PHV

Model (8)

$$\text{Rear End Conflicts/hr}_{\text{merge}} = 0.063 \times \text{PHV}_{\text{mainline}}^{0.680} \times \text{PHV}_{\text{merge}}^{0.385}$$

Degrees of Freedom	R-Squared R^2	Scaled Deviance	Pearson x^2	$x^2_{0.1,30}$	Shape Parameter
30	0.21	35.72	45.93	40.26	1.97

Variable	Coefficient
Constant	0.063
ADT $_{mainline}$	0.680
ADT $_{merge}$	0.385

Table 4.15 Prediction model of rear-end crashes as a function of mainline ADT and diverging ADT

Model (9) Rear-End Crashes/yr $_{diverge}$ = $0.098 \times ADT_{mainline}^{-0.038} \times ADT_{diverge}^{0.515}$					
Degrees of Freedom	**R-Squared R^2**	**Scaled Deviance**	**Pearson χ^2**	$\chi^2_{0.1,34}$	**Shape Parameter**
31	0.61	35.77	33.14	41.42	9.40
	Variable			**Coefficient**	
	Constant			0.098	
	$ADT_{mainline}$			-0.038	
	$ADT_{diverge}$			0.515	

Table 4.16 Prediction model of rear-end conflicts as a function of mainline PHV and diverging PHV

Model (10) Rear-End Conflicts/hr $_{diverge}$ = $3.68E\text{-}05 \times PHV_{mainline}^{1.163} \times PHV_{diverge}^{0.954}$					
Degrees of Freedom	**R-Squared R^2**	**Scaled Deviance**	**Pearson χ^2**	$\chi^2_{0.1,29}$	**Shape Parameter**
29	0.27	35.05	53.05	39.09	1.65
	Variable			**Coefficient**	
	Constant			3.68E-05	
	$VPH_{mainline}$			1.163	
	$VPH_{diverge}$			0.954	

4.5.2 Identification of Location Prone to Rear-End Incidents

Once the parameters of the prediction models were estimated, the models were then used to identify the crashes/conflict prone locations.

Comparison between rear-end crash and rear-end conflict prone locations at merge and diverge are shown in Tables 4.17 and Table 4.18 respectively and a summary was displayed in Table 4.19. Accordingly fewer locations were identified as accident prone by regression Models (7) and (9) based on actual crash than those identified by the regression Model (8) and (10) based on simulated conflicts records. Table 4.19 also showed that 5 APL was common between the crash/conflict models at merging and 2 at diverging location. This indicates a poor agreement between the rear-end crash and rear-end conflict models in identifying incident prone locations at both merging and diverging location. Table 4.20 shows the average rear-end crashes and rear-end conflicts based on incident proneness of locations.

4.5.3 Ranking Locations

The PFI and Ratio rankings (as explained in test 4) were then obtained using the rear-end crash prediction models, Models (7) and Model (9), and the corresponding rear-end conflict-prediction models, Model (8) and Model (10). Table (16) and Table (17) show the Spearman rank-correlations for both the Ratio and PFI rankings. These results indicated an insignificant correlation between diverging locations with “excessive rear-end incidents” and locations with “excessive rear end conflicts.” Moreover, the discussion of incident-prone ranking comparisons of Validation Test 4 is applicable here as well.

Table 4.17 Comparison between rear-end crash and rear-end conflict prone locations at merge

ID	Actual Rear-End Crash	Simulated Rear-End Conflict	Model Estimate (E(X))		EB Estimate		Crash Prone Location	Conflict Prone Location
			Crash	Conflict	Crash	Conflict		
1	4.0	70	4.1	203	4.0	71	no	no
1a	2.0	117	3.8	180	2.7	118	no	no
2	6.0	111	4.8	266	5.6	112	no	no
2a	3.7	158	4.7	261	4.0	159	no	no
3	0.7	50	7.6	410	2.4	52	no	no
4	2.7	721	8.7	531	4.1	720	no	**yes**
4a	7.3	663	8.6	514	7.6	662	no	**yes**
5	12.0	687	8.7	506	11.2	686	**yes**	**yes**
5a	4.3	365	8.5	452	5.3	365	no	**yes**
6	14.3	341	8.8	539	13.1	342	**yes**	**yes**
6a	3.7	268	8.0	438	4.7	269	no	no
7	17.7	707	9.0	454	15.7	706	**yes**	**yes**
7a	4.0	701	8.9	468	5.1	700	no	**yes**
8	10.7	366	9.1	536	10.3	367	**yes**	**yes**
8a	2.0	329	8.9	522	3.6	330	no	**yes**
9	5.7	113	6.5	314	5.9	114	no	no
9a	1.7	206	7.3	366	3.2	207	no	no
10a	3.7	252	7.4	364	4.6	253	no	no
11	8.7	445	7.7	384	8.4	445	no	**yes**
12	13.3	292	7.3	347	11.8	292	**yes**	no
12a	20.7	376	6.8	301	16.9	376	**yes**	**yes**
13	4.0	19	4.3	202	4.1	21	no	no
14a	3.3	156	5.1	256	3.9	157	no	no
15	7.7	255	4.0	187	6.2	254	no	no
15a	1.0	143	3.3	127	2.0	143	no	no
16a	5.7	1209	5.1	255	5.5	1202	no	**yes**
18	0.7	738	5.3	263	2.2	734	no	**yes**
18a	14.3	310	5.3	258	11.3	310	**yes**	no
19	1.7	54	5.1	252	2.8	56	no	no
19a	12.3	238	5.3	265	10.0	238	no	no
20	7.3	421	5.8	321	6.9	420	no	**yes**
20a	3.0	90	4.9	224	3.6	91	no	no
21	1.7	133	3.5	155	2.4	133	no	no

Spearman rank correlation based on Ratio ranking method = 0.041

Spearman rank correlation based on PFI ranking method = 0.026

Table 4.18 Comparison between rear-end crash and rear-end conflict prone locations at diverge

ID	Actual Total Crash	Simulated Total Conflict	Model Estimate (E(X))		EB Estimate		Crash Prone Location	Conflict Prone Location
			Crash	Conflict	Crash	Conflict		
1	5.3	127	6.5	244	6.0	128	no	no
1a	3.0	75	5.5	181	4.6	76	no	no
2	4.3	194	7.3	445	6.0	195	no	no
2a	5.0	251	6.9	423	6.1	252	no	no
3a	6.7	28	8.2	865	7.5	30	no	no
4	5.3	2291	7.4	1612	6.5	2290	no	**yes**
4a	6.3	2557	7.1	1489	6.8	2556	no	**yes**
5	8.0	1279	9.1	1599	8.5	1279	no	**yes**
5a	9.3	870	8.5	1207	8.9	870	no	**yes**
6	10.7	1593	8.6	1828	9.6	1593	no	**yes**
6a	5.3	739	6.5	1093	6.0	740	no	**yes**
7	11.7	1253	8.1	1160	9.8	1253	no	**yes**
7a	5.0	1678	8.0	1249	6.6	1677	no	**yes**
8	11.3	1624	11.2	1879	11.3	1624	**yes**	**yes**
8a	4.7	1287	10.5	1764	7.4	1287	no	**yes**
9	6.7	336	5.1	510	5.6	337	no	no
9a	6.0	435	6.9	743	6.5	436	no	no
10	12.7	1278	8.1	867	10.2	1277	no	**yes**
10a	2.7	844	7.7	750	5.4	844	no	**yes**
11	9.0	2118	8.2	847	8.6	2116	no	**yes**
11a	11.3	849	7.5	445	9.2	847	no	**yes**
12a	6.0	687	5.7	459	5.8	686	no	**yes**
13a	11.7	110	5.5	220	7.8	111	no	no
14b	2.0	177	7.1	388	4.9	178	no	no
15	7.7	119	5.5	194	6.3	120	no	no
15a	2.3	75	3.3	75	3.0	75	no	no
16a	14.7	2054	7.3	388	10.5	2047	**yes**	**yes**
18	1.7	186	7.1	402	4.7	187	no	no
18a	10.7	749	6.9	385	8.5	747	no	**yes**
19	1.7	236	6.9	367	4.7	237	no	no
19a	13.0	1630	7.3	416	9.8	1625	no	**yes**
20	12.0	225	9.5	670	10.8	226	**yes**	no
20a	8.3	194	6.0	277	6.9	194	no	no
21a	1.3	43	4.7	128	3.6	44	no	no

Spearman rank correlation based on Ratio ranking method = -0.159

Spearman rank correlation based on PFI ranking method = -0.040

Table 4.19 Summery of APLs of rear-end incidents

Incident Location	**merge**	**diverge**
Number of APLs identified based on rear-end crash	7	3
Number of APLs identified based on rear-end conflict	14	18
Common number of APLs identified based on both rear-end crash and conflict	5	2

Table 4.20 Average rear-end crashes and rear-end conflicts based on incident proneness of locations

Location	**Crash Prone**		**Conflict Prone**	
	Yes	**No**	**Yes**	**No**
Merge	14.7	4.2	576	160
Diverge	12.7	6.6	1410	176

5. Summary, Conclusions, and Recommendations

5.1 Summary and Conclusions

This study has provided the results of the field validation effort conducted to assess the safety of freeway merging and diverging locations by comparing conflicts predicted by SSAM with the actual crash experience. Twenty-two interchanges, forty-two merging and forty-two diverging locations for the field validation were selected. These locations were modeled in the VISSIM simulation system, and the simulation results were imported into SSAM to obtain a record of traffic conflicts based on the requirements on TTC and PET values. Several modeling assumptions were made including assumptions related to intersection geometry, speed profiles, vehicle type characteristics, traffic composition, and others. Crash records were obtained from Colorado Department of Transportation (CDOT) accident database.

Five statistical tests were applied to the data to quantify the correlation between interchange conflicts (from simulation) and interchange crashes (from CDOT database). The tests evaluated total incident (crash/conflict) frequencies and incident frequencies by maneuver type (lane change, or rear end). The crossing maneuver types were under-represented in the simulation due to the fact that the flow of traffic was in the same direction.

The tests included the following:

- Field Validation Test 1: Merging and diverging location ranking by total incidents.

- Field Validation Test 2: Merging and diverging location ranking by specific incident types.
- Field Validation Test 3: Crash and conflict prediction regression model paired comparison.
- Field Validation Test 4: Crash and conflict prediction regression model comparative analysis for total incidents
- Field Validation Test 4: Crash and conflict prediction regression model comparative analysis for specific type of incidents

In the first two field validation tests, the ranking derived from SSAM's conflict prediction model was compared to the ranking from the actual accident risk. The Spearman's rank correlation test was used to determine the level of agreement between the two ranks at the 90% confidence level. The Spearman correlation testing showed a significant correlation between total crashes and total conflicts, rear-end conflicts and rear-end crashes, between lane-change conflicts and lane-change crashes. Also, the rank correlation tests have shown correlation between ADT and the three incident types.

There were 1 percent merging and 4 percent diverging lane changing conflicts were recorded, while the remaining portion were rear end conflicts.
In all the simulation scenarios, rear-end conflict events made up the bulk of the total conflicts which was consistent with study reported on crash prediction models on urban signalized intersections, Guttman, Pu, Sayed, and Shelby (2008).

The crash and conflict prediction regression model paired comparison involved fitting a regression equation that relates actual crash to the SSAM predicted conflicts. The goodness-of-fit measure was tested using Scaled

deviance, Pearson chi-square, and the R-square value. Both the Pearson chi-squared and the scaled deviance values were not significant at the 90-percent confidence level, indicating a good fit. Moreover, these models were compared using the R-squared goodness-of-fit test (Miao, 1996), and the results conform to those of the Pearson chi-squared and the Scaled deviance. The relationship between total conflicts and total crashes exhibited a correlation (R-squared) of 0.57 and 0.90 for merging and diverging locations respectively.

However, as a benchmark basis for comparison, traditional safety assessments based on average daily traffic volumes were compared to the volume-based model and conflicts-based safety assessment. For crash prediction model based on volumes, the R-squared values were recorded to be 0.54 and 0.82 for merge and diverge approach respectively. Thus, both the volume-based model and the conflict based model exhibited comparable correlation. Moreover, both the volume-based model and the conflict based model had a better correlation than the traditional regression model in the previous researches.

In the volume-based model (ADT approach), merge and diverge locations that have the same ADT would have the same crash frequencies, which is not always true. On the contrary, looking at crash as a function of conflict, it explained the operational differences and vehicle dynamics of locations. Conflict models (SSAM) can be used to assess the relative safety of a pairs of merge/diverge design alternatives. Under equivalent traffic conditions (e.g., traffic volumes and truck percentage), for both merge/diverge design alternatives, SSAM could exhibit statistically significant differences in the total number of conflicts, the number of conflicts by type (crossing, lane-change, or

rear-end incidents). This helps to conclude that one design exhibited a higher frequency of conflicts, than the alternative design. This type of assessment helps the decision-making process about which design is the safer of the two.

Due to the fact that the increase in traffic volume is proportional to the occurrence of conflicts and crashes, both conflicts and crashes were correlated with interchange traffic volume. This effort found that the correlation between simulated conflicts and actual crashes were significant.

Crash and conflict prediction regression model comparative analysis for total incidents and for specific type of incidents involved the development of two prediction models relating the conflicts predicted by SSAM and the real-world crashes to traffic volume characteristics both at the merge and diverge locations. Due to zero number of observed crossing incidents, crossing-type incidents were excluded from this analysis. In addition, lane change type incidents were also excluded from the analysis because the models didn't converge to a finite value. This was perhaps due to the relatively low number of lane-changing crashes and conflicts.

The identification of crash-prone locations and conflict-prone locations were studied. This test determined whether the conflict prediction equation can predict risk in a manner similar to the crash prediction equation for interchanges with the same characteristics, by identifying accident prone locations (APL). Empirical Bayes (EB) method combines the information contained in crash counts of a specific highway segment with an estimate of its safety performance derived from safety performance function obtained from GLM models to increase the precision of estimation. Also, the EB method corrects for the regression-to-mean bias.

Comparison between crash prone locations and conflict prone locations at merge and diverge were compared, accordingly fewer locations were identified as accident prone by regression models based on actual crash than those identified by the regression model based on simulated conflicts records. It was showed that 5 APL and 2 APLs were common between the total crash/conflict models at merging and diverging location respectively. This indicates a poor agreement between the total crash and total conflict models in identifying incident prone locations at both merging and diverging location. The same conclusion is true for the rear-end and lane changing maneuvers.

The merging and diverging locations were then ranked in terms of priority for treatment once crash/conflict-prone sites were identified. Two techniques were used. The first ranking criterion, Ratio criterion, was calculated the ratio between the EB estimate and the predicted frequency as obtained from the GLM model (a risk-minimization objective). The second criterion, the cost effectiveness objective, was a “potential for improvement” (PFI) criterion, which was calculated as the difference between the observed crash/conflict frequency and the volume-based estimate of crash/conflict frequency. The Spearman rank-correlations for both the PFI and ratio rankings were very poor and non-significant at the 90% confidence level for total crash/conflict and specific types of incidents.

In general, the results of the validation effort of safety assessment based conflict analysis of simulated traffic at merging and diverging locations suggested that this technique showed great potential for interchange safety prediction.

5.2 Recommendations

For the last two decades, several legislations have been making safety a central, explicit, comprehensive, and integrated part of transportation planning. These legislations have encouraged or insisted on giving safety priority through better data, better analysis, better reporting systems, and the adoption of a structured comprehensive approach. A detailed study of the safety of highways would help to understand safety and help to make safety legislation a success.

The SSAM approach demonstrated significant correlation with actual crash date. Project planners and engineers of current projects use a well-developed safety performance functions provided in this dissertation to get realistic estimates of expected safety performance of merge/diverge locations. SSAM provides a new option to assess the safety of traffic facilities that have not yet been constructed and traffic control policies that have not yet been enacted in the field. It is also applicable to facilities where traditional, volume based crash-prediction models (and norms) have not been established thus the SSAM approach exhibited great promise. Understanding of the safety and design of future projects would eliminate wasting time and money on improvements that soon will become inadequate or inappropriate.

During the modeling process, it was observed that there was abrupt lane-changing behavior. To reduce this behavior certain measures were taken such as extending the lengths of each approach (model link) which provides vehicles with significantly more time to decide on their route decision. Moreover, VISSIM's lane changing algorithm needs to be revised to eliminate the abrupt lane-changing behavior that occurred during traffic simulation

modeling. Such an abrupt behavior can increase the number of conflicts unrealistically.

The field validation test exhibited a distribution of conflicts by type that lean more heavily toward rear-end incident (less dangerous events) than the distribution of events found in actual crash records. It is difficult to explain whether this discrepancy is due to shortcomings in the underlying simulations model (VISSIM), the conflict analysis tool (SSAM), or if the conflict occurrence in the field does indeed differ from crash occurrence. Therefore, in order to reconcile these facts much remains to be done in the future to study, analyze and quantify the shortcomings of simulated conflict data versus real-world crash data including any potential shortcomings of the current traffic safety analysis method. It is hoped that this dissertation will serve as a basis for future research in this direction.

APPENDIX

Dataset

A. Interchange traffic flow information

B. Average 3 year crashes recorded at merge and diverge locations

C. Average yearly crashes recorded at merge and diverge locations

D. Conflicts of five replications at merge and diverge locations recorded by SSAM

E. Average hourly conflicts at merge and diverge locations recorded by SSAM

Appendix A Interchange traffic flow information

<table>
<tr><th rowspan="2">HWY NO</th><th colspan="3">Interchange</th><th colspan="2">ADT</th><th colspan="2">PHV</th></tr>
<tr><th>ID</th><th>Name</th><th>Traffic Direction</th><th>Mainline</th><th>On/Off Ramp</th><th>Mainline</th><th>On/Off Ramp</th></tr>
<tr><td rowspan="24">I-25</td><td>1</td><td>Ridgegate Pkwy</td><td>NB</td><td>47,500</td><td>7,650</td><td>3,800</td><td>612</td></tr>
<tr><td>1a</td><td>(truck=8.2%)</td><td>SB</td><td>47,500</td><td>5,600</td><td>3,800</td><td>448</td></tr>
<tr><td>2</td><td>E Lincoln Ave</td><td>NB</td><td>55,000</td><td>9,720</td><td>4,400</td><td>960</td></tr>
<tr><td>2a</td><td>(truck=7.1%)</td><td>SB</td><td>55,000</td><td>8,650</td><td>4,400</td><td>910</td></tr>
<tr><td>3</td><td>E County Line Rd</td><td>NB</td><td>86,500</td><td>15,100</td><td>6,920</td><td>1,330</td></tr>
<tr><td>3a</td><td>(truck=7.1%)</td><td>SB</td><td>86,500</td><td>12,560</td><td>6,920</td><td>1,110</td></tr>
<tr><td>4</td><td>E Dry Creek Rd</td><td>NB</td><td>110,500</td><td>10,430</td><td>9,945</td><td>1,370</td></tr>
<tr><td>4a</td><td>(truck=6.6%)</td><td>SB</td><td>110,500</td><td>9,640</td><td>9,945</td><td>1,260</td></tr>
<tr><td>5</td><td>E Arapahoe Ave</td><td>NB</td><td>100,500</td><td>15,400</td><td>8,040</td><td>1,760</td></tr>
<tr><td>5a</td><td>(truck=6.1%)</td><td>SB</td><td>100,500</td><td>13,500</td><td>8,040</td><td>1,310</td></tr>
<tr><td>6</td><td>E Orchard Rd</td><td>NB</td><td>105,000</td><td>14,060</td><td>8,400</td><td>1,920</td></tr>
<tr><td>6a</td><td>(truck=5.8%)</td><td>SB</td><td>105,000</td><td>8,205</td><td>8,400</td><td>1,120</td></tr>
<tr><td>7</td><td>E Belleview Ave</td><td>NB</td><td>110,500</td><td>12,542</td><td>8,840</td><td>1,120</td></tr>
<tr><td>7a</td><td>(truck=5.1%)</td><td>SB</td><td>110,500</td><td>12,058</td><td>8,840</td><td>1,210</td></tr>
<tr><td>8</td><td>E Hampden Ave</td><td>NB</td><td>96,500</td><td>23,200</td><td>7,720</td><td>2,190</td></tr>
<tr><td>8a</td><td>(truck=3.9%)</td><td>SB</td><td>96,500</td><td>20,360</td><td>7,720</td><td>2,050</td></tr>
<tr><td>9</td><td>E Yale Ave</td><td>NB</td><td>93,500</td><td>4,930</td><td>7,480</td><td>580</td></tr>
<tr><td>9a</td><td>(truck=4.5%)</td><td>SB</td><td>93,500</td><td>8,941</td><td>7,480</td><td>860</td></tr>
<tr><td>10</td><td>E Evans Ave</td><td>NB</td><td>90,000</td><td>12,150</td><td>7,200</td><td>1,060</td></tr>
<tr><td>10a</td><td>(truck=3.9%)</td><td>SB</td><td>90,000</td><td>11,000</td><td>7,200</td><td>910</td></tr>
<tr><td>11</td><td>S Colorado Blvd</td><td>NB</td><td>91,000</td><td>12,650</td><td>7,280</td><td>1,020</td></tr>
<tr><td>11a</td><td>(truck=6.1%)</td><td>SB</td><td>91,000</td><td>10,600</td><td>7,280</td><td>520</td></tr>
<tr><td>12</td><td>University Blvd</td><td>NB</td><td>93,500</td><td>8,769</td><td>7,480</td><td>750</td></tr>
<tr><td>12a</td><td>(truck=6.3%)</td><td>SB</td><td>93,500</td><td>6,190</td><td>7,480</td><td>520</td></tr>
<tr><td rowspan="14">I-225</td><td>13</td><td>E Yosemite Ave</td><td>NB</td><td>53,000</td><td>6,037</td><td>4,240</td><td>500</td></tr>
<tr><td>13a</td><td>(truck=5.9%)</td><td>SB</td><td>53,000</td><td>5,640</td><td>4,240</td><td>480</td></tr>
<tr><td>14</td><td>S Parker Rd</td><td>NB</td><td>60,000</td><td>10,030</td><td>4,800</td><td>802</td></tr>
<tr><td>14a</td><td>(truck=5.9%)</td><td>SB</td><td>60,000</td><td>9,350</td><td>4,800</td><td>748</td></tr>
<tr><td>15</td><td>E Iliff Ave</td><td>NB</td><td>50,500</td><td>5,572</td><td>4,040</td><td>446</td></tr>
<tr><td>15a</td><td>(truck=7.1%)</td><td>SB</td><td>50,500</td><td>2,057</td><td>4,040</td><td>165</td></tr>
<tr><td>16</td><td>E Mississippi Ave</td><td>NB</td><td>58,500</td><td>9,570</td><td>4,680</td><td>766</td></tr>
<tr><td>16a</td><td>(truck=6.5%)</td><td>SB</td><td>58,500</td><td>9,640</td><td>4,680</td><td>771</td></tr>
<tr><td>17</td><td>E Alameda Ave</td><td>NB</td><td>60,000</td><td>12,571</td><td>4,800</td><td>1,030</td></tr>
<tr><td>17a</td><td>(truck=6.5%)</td><td>SB</td><td>60,000</td><td>10,681</td><td>4,800</td><td>910</td></tr>
<tr><td>18</td><td>6th Ave</td><td>NB</td><td>63,000</td><td>9,140</td><td>5,040</td><td>731</td></tr>
<tr><td>18a</td><td>(truck=7.2%)</td><td>SB</td><td>63,000</td><td>8,750</td><td>5,040</td><td>700</td></tr>
<tr><td>19</td><td>E Colfax Ave</td><td>NB</td><td>61,000</td><td>8,650</td><td>4,880</td><td>692</td></tr>
<tr><td>19a</td><td>(truck=7.0%)</td><td>SB</td><td>61,000</td><td>9,862</td><td>4,880</td><td>789</td></tr>
<tr><td rowspan="4">I-70</td><td>20</td><td>Kipling St</td><td>EB</td><td>61,000</td><td>16,245</td><td>4,880</td><td>1,300</td></tr>
<tr><td>20a</td><td>(truck=9.4%)</td><td>WB</td><td>61,000</td><td>6,576</td><td>4,880</td><td>526</td></tr>
<tr><td>21</td><td>Sheridan Blvd</td><td>EB</td><td>46,300</td><td>3,945</td><td>3,700</td><td>316</td></tr>
<tr><td>21a</td><td>(truck=4.5%)</td><td>WB</td><td>46,300</td><td>4,000</td><td>3,700</td><td>320</td></tr>
</table>

Appendix B Average 3 year crashes recorded at merge and diverge

HWY NO	Interchange			Three Year Crash Record											
				merge						diverge					
	ID	Name	Mile Post	NB/EB			SB/WB			NB/EB			SB/WB		
				RE	LC	Total	RE	LC	Total	RE	LC	Total	RE	LC	Total
I-25	1	Ridgegate Pkwy	192.07	12	2	14	6	5	11	16	5	21	9	3	12
	2	E Lincoln Ave	192.99	18	4	22	11	4	15	13	2	15	15	8	23
	3	E County Line Rd	195.13	2	8	10	-	-	-	-	-	-	20	2	22
	4	E Dry Creek Rd	196.14	8	8	16	22	10	32	16	5	21	19	11	30
	5	E Arapahoe Ave	197.19	36	23	59	13	8	21	24	8	32	28	12	40
	6	E Orchard Rd	198.29	43	10	53	11	4	15	32	6	38	16	5	21
	7	E Belleview Ave	199.39	53	10	63	12	8	20	35	12	47	15	11	26
	8	E Hampden Ave	201.58	32	7	39	6	14	20	34	8	42	14	11	25
	9	E Yale Ave	202.64	17	4	21	5	1	6	20	4	24	18	9	27
	10	E Evans Ave	203.54	-	-	-	11	12	23	38	8	46	8	9	17
	11	S Colorado Blvd	204.04	26	7	33	-	-	-	27	9	36	34	7	41
	12	University Blvd	205.06	40	8	48	62	4	66	56	16	72	18	4	22
I-225	13	E Yosemite Ave	1.33	12	5	17	-	-	-	-	-	-	35	6	41
	14	S Parker Rd	3.95	17	5	22	10	4	14	31	4	35	6	4	10
	15	E Iliff Ave	5.37	23	7	30	3	4	7	23	5	28	7	3	10
	16	E Mississippi Ave	6.89	26	7	33	17	4	21	29	4	33	44	4	48
	17	E Alameda Ave	7.85	19	5	24	5	1	6	15	5	20	33	4	37
	18	6th Ave	8.96	2	6	8	43	7	50	5	8	13	32	4	36
	19	E Colfax Ave	9.90	5	4	9	37	6	43	5	8	13	39	7	46
I-70	20	Kipling St	267.41	22	4	26	9	7	16	36	10	46	25	4	29
(EB:WB)	21	Sheridan Blvd	270.50	5	8	13	-	-	-	-	-	-	4	7	11
Sum				418	142	560	283	103	386	455	127	582	439	135	574
Average Yearly Crashes by Type				19.9	6.8	26.7	13.5	4.9	18.4	21.7	6.0	27.7	20.9	6.4	27.3
Percentage of Crashes by Type				75	25	100	73	27	100	78	22	100	76	24	100

where: LC= lane change , RE= rear-end; NB, SB, EB,WB =north bound, south bound, east bound and west bound respectively.

Appendix C Average yearly crashes recorded at merge and diverge

HWY NO	Interchange			Average Yearly Crash											
	ID	Name	Mile Post	merge						diverge					
				NB/EB			SB/WB			NB/EB			SB/WB		
				RE	LC	Total	RE	LC	Total	RE	LC	Total	RE	LC	Total
I-25	1	Ridgegate Pkwy	192.07	4.0	0.7	4.7	2.0	1.7	3.7	5.3	1.7	7.0	3.0	1.0	4.0
	2	E Lincoln Ave	192.99	6.0	1.3	7.3	3.7	1.3	5.0	4.3	0.7	5.0	5.0	2.7	7.7
	3	E County Line Rd	195.13	0.7	2.7	3.3	-	-	-	-	-	-	6.7	0.7	7.3
	4	E Dry Creek Rd	196.14	2.7	2.7	5.3	7.3	3.3	10.7	5.3	1.7	7.0	6.3	3.7	10.0
	5	E Arapahoe Ave	197.19	12.0	7.7	19.7	4.3	2.7	7.0	8.0	2.7	10.7	9.3	4.0	13.3
	6	E Orchard Rd	198.29	14.3	3.3	17.7	3.7	1.3	5.0	10.7	2.0	12.7	5.3	1.7	7.0
	7	E Belleview Ave	199.39	17.7	3.3	21.0	4.0	2.7	6.7	11.7	4.0	15.7	5.0	3.7	8.7
	8	E Hampden Ave	201.58	10.7	2.3	13.0	2.0	4.7	6.7	11.3	2.7	14.0	4.7	3.7	8.3
	9	E Yale Ave	202.64	5.7	1.3	7.0	1.7	0.3	2.0	6.7	1.3	8.0	6.0	3.0	9.0
	10	E Evans Ave	203.54	-	-	-	3.7	4.0	7.7	12.7	2.7	15.3	2.7	3.0	5.7
	11	S Colorado Blvd	204.04	8.7	2.3	11.0	-	-	-	9.0	3.0	12.0	11.3	2.3	13.7
	12	University Blvd	205.06	13.3	2.7	16.0	20.7	1.3	22.0	18.7	5.3	24.0	6.0	1.3	7.3
I-225	13	E Yosemite Ave	1.33	4.0	1.7	5.7	-	-	-	-	-	-	11.7	2.0	13.7
	14	S Parker Rd	3.95	5.7	1.7	7.3	3.3	1.3	4.7	10.3	1.3	11.7	2.0	1.3	3.3
	15	E Iliff Ave	5.37	7.7	2.3	10.0	1.0	1.3	2.3	7.7	1.7	9.3	2.3	1.0	3.3
	16	E Mississippi Ave	6.89	8.7	2.3	11.0	5.7	1.3	7.0	9.7	1.3	11.0	14.7	1.3	16.0
	17	E Alameda Ave	7.85	6.3	1.7	8.0	1.7	0.3	2.0	5.0	1.7	6.7	11.0	1.3	12.3
	18	6th Ave	8.96	0.7	2.0	2.7	14.3	2.3	16.7	1.7	2.7	4.3	10.7	1.3	12.0
	19	E Colfax Ave	9.90	1.7	1.3	3.0	12.3	2.0	14.3	1.7	2.7	4.3	13.0	2.3	15.3
I-70	20	Kipling St	267.41	7.3	1.3	8.7	3.0	2.3	5.3	12.0	3.3	15.3	8.3	1.3	9.7
	21	Sheridan Blvd	270.50	1.7	2.7	4.3	-	-	-	-	-	-	1.3	2.3	3.7
Sum				139	47	187	94	34	129	152	42	194	146	45	191
Average Yearly Crashes by Type				6.6	2.3	8.9	4.5	1.6	6.1	7.2	2.0	9.2	7.0	2.1	9.1
Percentage of Crashes by Type				75	25	100	73	27	100	78	22	100	76	24	100

where: LC= lane change , RE= rear-end; NB, SB, EB,WB =north bound, south bound, east bound and west bound respectively.

Appendix D Conflicts of five replications at merge and diverge locations recorded by SSAM

HWY NO	Interchange			Number of Conflicts in Five Replications											
	ID	Name	Mile Post	merge						diverge					
				NB/EB			SB/WB			NB/EB			SB/WB		
				RE	LC	Total	RE	LC	Total	RE	LC	Total	RE	LC	Total
I-25	1	Ridgegate Pkwy	192.07	349	0	349	585	0	585	637	0	637	375	0	375
	2	E Lincoln Ave	192.99	556	0	556	791	0	791	648	21	669	1,158	95	1,253
	3	E County Line Rd	195.13	252	16	268	-	-	-	-	-	-	126	14	140
	4	E Dry Creek Rd	196.14	3,603	0	3,603	3,314	0	3,314	10,024	1,432	11,456	11,765	1,022	12,787
	5	E Arapahoe Ave	197.19	3,435	31	3,466	1,825	0	1,825	5,591	801	6,392	3,860	491	4,351
	6	E Orchard Rd	198.29	1,706	62	1,768	1,342	0	1,342	6,905	1,058	7,963	3,115	578	3,693
	7	E Belleview Ave	199.39	3,535	60	3,595	3,503	6	3,509	5,702	566	6,268	7,911	483	8,394
	8	E Hampden Ave	201.58	1,829	0	1,829	1,645	11	1,656	8,109	11	8,120	5,977	459	6,436
	9	E Yale Ave	202.64	565	0	565	1,029	5	1,034	1,592	89	1,681	2,065	109	2,174
	10	E Evans Ave	203.54	-	-	-	1,260	5	1,265	6,008	381	6,389	3,748	471	4,219
	11	S Colorado Blvd	204.04	2,225	0	2,225	-	-	-	9,750	840	10,590	4,014	236	4,250
	12	University Blvd	205.06	1,462	0	1,462	1,878	0	1,878	2,781	261	3,042	3,265	170	3,435
I-225	13	E Yosemite Ave	1.33	95	9	104	-	-	-	-	-	-	551	0	551
	14	S Parker Rd	3.95	23,775	271	24,046	780	0	780	44,715	304	45,019	885	0	885
	15	E Iliff Ave	5.37	1,276	5	1,281	715	0	715	581	16	597	374	0	374
	16	E Mississippi Ave	6.89	26,033	509	26,542	6,045	155	6,200	27,230	201	27,431	10,012	254	10,266
	17	E Alameda Ave	7.85	37,995	292	38,287	39,537	316	39,853	24,845	242	25,087	21,235	116	21,351
	18	6th Ave	8.96	3,690	41	3,731	1,551	10	1,561	904	26	930	3,656	92	3,748
	19	E Colfax Ave	9.90	271	0	271	1,188	10	1,198	1,095	85	1,180	8,090	59	8,149
I-70	20	Kipling St	267.41	2,104	35	2,139	452	0	452	1,035	90	1,125	939	31	970
(EB:WB)	21	Sheridan Blvd	270.50	663	10	673	-	-	-	-	-	-	217	0	217
Sum				115,419	1,341	116,760	67,440	518	67,955	158,455	6,421	164,875	93,338	4,680	98,010
Average (per merge/diverge location)				5,771	67	5,838	3,967	30	3,997	8,803	357	9,160	4,445	223	4,667
Percentage (by type)				99	1	100	99	1	100	96	4	100	95	5	100

where: LC= lane change , RE= rear-end; NB, SB, EB,WB =north bound, south bound, east bound and west bound respectively.

Appendix E Average hourly conflicts at merge and diverge locations recorded by SSAM

HWY NO	Interchange			Average Hourly Conflicts											
	ID	Name	Mile Post	merge						diverge					
				NB/EB			SB/WB			NB/EB			SB/WB		
				RE	LC	Total	RE	LC	Total	RE	LC	Total	RE	LC	Total
I-25	1	Ridgegate Pkwy	192.07	70	0	70	117	0	117	127	0	127	75	0	75
	2	E Lincoln Ave	192.99	111	0	111	158	0	158	190	4	194	232	19	251
	3	E County Line Rd	195.13	50	3	53	-	-	-	-	-	-	25	3	28
	4	E Dry Creek Rd	196.14	721	0	721	663	0	663	2,005	286	2,291	2,353	204	2,557
	5	E Arapahoe Ave	197.19	687	6	693	365	0	365	1,119	160	1,279	772	98	870
	6	E Orchard Rd	198.29	341	12	353	268	0	268	1,381	212	1,593	623	116	739
	7	E Belleview Ave	199.39	707	12	719	701	1	702	1,140	113	1,253	1,582	96	1,678
	8	E Hampden Ave	201.58	366	0	366	329	2	331	1,622	2	1,624	1,195	92	1,287
	9	E Yale Ave	202.64	113	0	113	206	1	207	318	18	336	413	22	435
	10	E Evans Ave	203.54	-	-	-	252	1	253	1,202	76	1,278	750	94	844
	11	S Colorado Blvd	204.04	445	0	445	-	-	-	1,950	168	2,118	803	46	849
	12	University Blvd	205.06	292	0	292	376	0	376	556	52	608	653	34	687
I-225	13	E Yosemite Ave	1.33	19	2	21	-	-	-	-	-	-	110	0	110
	14	S Parker Rd	3.95	4,755	54	4,809	156	0	156	8,943	61	9,004	177	0	177
	15	E Iliff Ave	5.37	255	1	256	143	0	143	116	3	119	75	0	75
	16	E Mississippi Ave	6.89	5,207	102	5,309	1,209	31	1,240	5,446	40	5,486	2,002	52	2,054
	17	E Alameda Ave	7.85	7,599	58	7,657	7,907	63	7,970	4,969	49	5,018	4,247	23	4,270
	18	6th Ave	8.96	738	8	746	310	2	312	181	5	186	731	18	749
	19	E Colfax Ave	9.90	54	0	54	238	2	240	219	17	236	1,618	12	1,630
I-70	20	Kipling St	267.41	421	7	428	90	0	90	207	18	225	188	6	194
(EB:WB)	21	Sheridan Blvd	270.50	133	2	135	-	-	-	-	-	-	43	0	43
Sum				23,084	267	23,351	13,488	103	13,591	31,691	1,284	32,975	18,667	935	19,602
Average (per merge/diverge location)				1,154	13	1,168	793	6	799	1,761	71	1,832	889	45	933
Percentage (by type)				99	1	100	99	1	100	96	4	100	95	5	100

where: LC= lane change , RE= rear-end; NB, SB, EB,WB =north bound, south bound, east bound and west bound respectively.

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